Psychopathology networks
ISBP Summer School

Talya Greene
Community Mental Health
University of Haifa
Networks

• ‘Trendy’ topic
• Complex systems
• Computing, biology, social sciences, neuroscience, economics
• Psychopathology networks – Probably > 150 papers. Increasing exponentially
Overview

• Network theory and psychopathology
• Terminology – ways to interpret a network
• Cross-sectional and intensive longitudinal networks
  • Examples
• Questions/discussion
Resources

- http://psychosystems.org/
- http://eiko-fried.com/
- http://sachaepskamp.com/

The Psych Systems Project
What is a network?

• A network consists of different entities that are connected in some way
Psychopathology networks
Common cause model

• Robert Koch 1905–Received Nobel Prize
• Microbiologist – identified specific causative agents of specific diseases
  • E.g., TB, cholera, anthrax
• Emil Kraepelin – Argued Dementia Praecox = neurobiological origin

• Disorder/disease causes symptoms.
Common cause model

- Assumption = a latent causal factor
- Symptoms result from this cause
- We observe the symptoms and often infer cause
What could the common cause be here?
Network perspective and psychopathology

• Common cause/latent variable approaches are flawed
• Symptoms interact in meaningful ways
• Symptoms are not interchangeable
• These symptoms can be understood as a causal system
• The symptoms constitute the disorder rather than resulting from the disorder
• McNally (2016): Network analysis could potentially transform understanding and treatment of psychopathology
Network perspective

- Traditional: symptoms cluster because of a shared origin
- Network: symptoms cluster because they influence each other

http://eiko-fried.com/vgct2017/
Hybrid models

- ONSET: Trauma → Acute stress/PTSD symptoms
- Build-up or maintenance of symptoms

Network terminology
Network theory

Network models are statistical models and need to be clearly distinguished from network theory

SPECIAL ARTICLE

A network theory of mental disorders

Denny Borsboom
Department of Psychology, University of Amsterdam, Amsterdam 1018 XA, The Netherlands

Exploratory

- Networks are exploratory
- **Generate hypotheses**
- Can’t be use to confirm hypotheses
Terminology

• Entities are called **nodes**
  Can be anything – person, train station, behavior, symptom

• Connections are called **edges**
  Represent a relationship – interaction, effect, distance, etc.
Psychological networks

In psychological networks, nodes are items (e.g., symptoms, emotions), and edges are statistical relationships.

Unlike social networks, edges are unobserved and therefore need to be estimated.

http://eiko-fried.com/vgct2017/
Edge weights

• Edges can *weighted* to represent the strength of the relationship
• Weights are represented by line thickness
Signs of edges

- Edges can have a sign
- Usually coloured to show positive or negative associations
- Typically green/blue = positive and red = negative
Directed edges

Networks can be *undirected* or *directed*
Centrality

• A central symptom is one that is important to the network – highly connected
• Activating this symptom could spread symptom activation throughout the network
• Peripheral symptoms have fewer connections and less influence on the network
Centrality

• Centrality represents the connectedness of a given symptom with all other symptoms in the network

• **Node strength centrality / degree centrality**: sum of all direct associations a given symptom exhibits with all other nodes

• **Betweenness centrality**: how many times a symptom lies along the shortest paths between other pairs of symptoms

• **Closeness centrality**: inverse of the sum of all shortest paths between a node and all other nodes in the network
Expected influence

- New metric – expected influence
- The sum of all edges extending from a given node (maintaining the sign)
Important *R*-packages

Commonly use R and the program R-Studio

- **qgraph**: estimation and visualization of correlation networks, partial correlation networks, and GGMs
- **IsingFit**: estimation of Ising Models
- **bootnet**: testing the stability of networks
- **mlvar**: multilevel models
- **networktools**: Expected influence and bridge centrality
- And more – **graphicalVAR, igraph**
- Also JASP - https://jasp-stats.org/2018/03/20/perform-network-analysis-jasp/
Visualization in qgraph

• In qgraph, the Fruchterman-Reingold algorithm is used that iteratively computes optimal placement of nodes
  • Most central nodes will end up more in the center, least central nodes more in the periphery
• Can’t interpret the network just by looking at it.
• Need the centrality indices
Conditional independence

• Not just interested in the relationships between nodes, but in the unique effects between them having controlled for the effects of the others (e.g., multiple regression)

• Conditional independence relationships - in networks we want to know how symptoms A and B are related after controlling for all other symptoms
Conditional independence

Correlation network

Partial correlation network

Regularization

• Solution: estimate networks (Gaussian graphic models) with the **least absolute shrinkage and selection operator** (lasso)

• The lasso shrinks all regression coefficients, and small ones are set to zero (drop out of the model)
  • Interpretability: only relevant edges retained in the network
  • Stability/replicability: avoids obtaining *spurious* edges only due to chance
  • We also have fewer parameters to estimate

• Regularization returns a **sparse network**: few edges are used to explain the covariation structure in the data (parsimony)
Gaussian Graphical Model (GGM)
Cross-sectional networks

- Correlation network/partial correlation/regularized GGM network
- Undirected
- Weighted
- Between-persons (average effects)
- Subject to all the limitations of cross-sectional research
Treatment-seeking veterans PTSD

Comorbidity
Comorbidity

- E = Stressor
- Develops disorder X in reaction to E
- Then bridge symptoms B
- And finally disorder Y

- Can conceptualize X as MDD
- Y as GAD
- Bridge symptoms = sleep, fatigue, concentration problems

Fig 1. Empirical network of 120 psychiatric symptoms.

Bridge connections

Time-series models

• N=1
• N>1
• Use a vector auto-regressive (VAR) model
• Lagged relationships
• Can be applied to 1 person or multiple people (multi-level)
• Intensive longitudinal data: e.g. repeated assessments over a short time period (daily diary, ESM, EMA etc.), often use smartphones
• Directed edges
• Can’t make causal inferences, but can infer potential causal relations
Temporal and contemporaneous networks

- Temporal = lagged relations
- Contemporaneous = within time window associations
- Temporal relations estimated first.
• Directed networks allow for estimation of in-strength and out-strength

• In-strength = the extent to which a given node is predicted by the other nodes at the previous measurement

• Out-strength = the extent to which a given node predicts other nodes at the previous measurement

• Auto-regressive symptoms – symptoms which predict themselves at the following measurement
Idiographic networks n=1

- Clinical patient – 47 ESM reports over two weeks

N>1 networks

Contemporaneous

Temporal
Limitations

• Not yet modeling time varying processes (coming soon)
• Few replications
• Missing nodes? Misrepresent the networks
• Power
• Heterogeneity – don’t (yet) have network mixture models (probably need very large samples)
• Exploratory – therefore not necessarily generalizable
• Emerging field with many unanswered questions
Future directions
Idiographic networks for treatment?

• First stages
• Rubel et al. 2017 – translating n=1 network models into personalized treatments by developing a treatment algorithm
• Van der Veen, Riese, Kroeze - choose items to track, then discuss the networks with the patients as treatment tool
• Bastiaansen et al. (in preparation) – time-series data from one patient to many analysts – little agreement on treatment approach
Expanded network approach

Payton Jones (2017)

Networks of problems

Conclusions

• Important to separate between network theory and network models
• Network models have potential to gain insight into symptom level relations, potentially causal interactions, comorbidity, among others
• Can generate hypotheses about between-person processes, and also within-person processes
• Can help us to understand comorbidity
• Potential clinical application
Thank you!

Email: tgreene@univ.haifa.ac.il
Twitter: @talyagreene

Brain and Behavior Research Foundation
Narsad Young Investigator Award
The Moshe Hess Foundation
Israel Science Foundation
Dynamic networks during conflict

- 2014 Israel-Gaza Conflict (8 July- 26 August)
- Airstrikes, ground invasion from Israel to Gaza
- Rockets, mortars, tunnels from Gaza to Israel
- Participant accessibility

Dynamic networks of PTSD symptoms during conflict

Talya Greene¹, Marc Gelkopf²,³, Sacha Epskamp¹ and Eiko Fried¹

¹Department of Community Mental Health, University of Haifa, Haifa, Israel; ²NATAL, Israel Trauma Center for Victims of Terror and War, Tel Aviv, Israel and ³Department of Psychology, University of Amsterdam, Amsterdam, The Netherlands
Overview

• General population sample of Israeli adult civilians exposed to rocket fire (n=96) (part of a larger study)
• Twice-daily ESM reports of PTSD symptoms via smartphone for 30 days (Greene et al., 2017)
• Multilevel vector auto-regression model in R
Dynamic PTSD networks during conflict

Contemporaneous

Temporal

Intrusions
1: Intrusive thoughts
2: Nightmares
3: Flashbacks
4: Emotional cue reactivity
5: Physiological cue reactivity

Avoidance
6: Avoidance of thoughts
7: Avoidance of reminders

Negative alterations in mood and cognitions
8: Trauma-related amnesia
9: Negative beliefs
10: Blame of self or others
11: Negative trauma-related emotions
12: Loss of interest
13: Detachment
14: Restricted affect

Alterations in arousal and reactivity
15: Irritability/anger
16: Self-destructive/reckless behavior
17: Hypervigilance
18: Exaggerated startle response
19: Difficulty concentrating
20: Sleep disturbance
Contemporaneous network (within time window)

Mostly positive (blue edges)

Some pairs strongly associated:
- Hypervigilance (17) ↔ startle (18)
- Avoidance thoughts (6) ↔ amnesia (8)
- Loss of interest (12) ↔ detachment (13)

Close to DSM-5 clusters

Exceptions
- Amnesia (8) - avoidance
- Anger (15) - negative mood and cognitions
Temporal network (lagged associations)

Some negative edges (red)
Blame (10)

Out-strength – symptoms which predict other symptoms at the next measurement (intervention targets?)
Startle (18), Blame (10), restricted affect (14), negative emotions (11), avoidance of thoughts (6)

In-strength – influenced by other variables at the previous measurement
Sleep disturbance (20), loss of interest (12)

Strong auto-correlations
Startle (18), Hypervigilance (17)