Network modeling of psychological processes
From exploration to theory formation

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EMPG 2018
The Network Perspective


The Network Perspective


Analogy 1: Ecology

Analogy 2: Ferromagnetism
The Ising model:
Analogy 3: Psychopathology as a Virus

Video...
Markov Random Fields
A graph is a set $G$ consisting of two sets: \( V \) (set of nodes) and \( E \) (set of edges).

**Markov Random Fields**

- $X_i \bot \bot X_j \mid X - (i, j) \iff (i, j) \not\in E$

- Graphical representation: Two variables are connected if they are not conditionally independent.

- Powerful characterization of joint likelihood between observed variables.
A graph is a set $G$ consisting of two sets: $V$ (set of nodes) and $E$ (set of edges).

$$G = \{V, E\}$$

$$V = \{1, 2, 3\}$$

$$E = \{(1, 2), (2, 3)\}$$
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$$V = \{1, 2, 3\}$$
$$E = \{(1, 2), (2, 3)\}$$

Markov Random Fields

$$X_i \perp \perp X_j \mid X_{-(i,j)} = x_{-(i,j)} \iff (i,j) \notin E$$

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- Powerful characterization of joint likelihood between observed variables.
Markov Random Fields

In MRFs, weights should indicate conditional independence:

\[ X_i \perp \perp X_j \mid X_{\neq (i,j)} \]

\[ \iff \omega_{ij} = 0 \]

Furthermore, positive weights should be comparable to negative weights in strength of association.
Weighted graphs

A weighted graph uses a *weights matrix* to characterize the strength of connection:

\[ \Omega = \begin{bmatrix} 0 & 0.5 & 0 \\ 0.5 & 0 & -0.3 \\ 0 & -0.3 & 0 \end{bmatrix} \]

Positive edges are drawn blue (or green) and negative edges red.
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In MRFs, weights should indicate conditional independence:

\[X_i \perp \!\!\!\!\!\!\!\!\!\perp X_j \mid X_{- (i,j)} = x_{- (i,j)} \iff \omega_{ij} = 0\]

Furthermore, positive weights should be comparable to negative weights in strength of association.
Markov Random Field

In a Markov random field (MRF) a joint probability distribution is formed by multiplying potential functions $\phi_C (x_C) \geq 0$ for every clique in a graph (e.g., one variable, two connected variables, a set of three connected variables):

$$\text{Pr} (X = x) \propto \prod_{C \in \text{cl}(G)} \phi_C (x_C)$$
Markov Random Field

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\[
\text{Pr} (\mathbf{X} = \mathbf{x}) \propto \prod_{C \in \text{cl}(G)} \phi_C (x_C)
\]

Pairwise MRFs only include potential function up to pairwise interactions:

\[
\text{Pr} (\mathbf{X} = \mathbf{x}) \propto \prod_i \phi_i (x_i) \prod_{<ij>} \phi_{ij} (x_i, x_j)
\]

These are typically used in network psychometrics.
Suppose random variable $X$ with realization $x$ can take two outcomes: $s_1$ and $s_2$. We can make use of a potential function to map a unique weight to each outcome:

$$
\phi(x) = \begin{cases} 
a & \text{if } x = s_1 \\
b & \text{if } x = s_2 
\end{cases}
$$
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We can use this potential function to characterize a likelihood function for $X$:

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\Pr(X = x) \propto \phi(x)
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\phi(x) = \begin{cases} 
a & \text{if } x = s_1 \\
1/a & \text{if } x = s_2
\end{cases}
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$$
\Pr(X = x) \propto \phi(x)
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We can add a different potential function for $X_2$:

$$\Pr(X_1 = x_1, X_2 = x_2) \propto \phi_1(x_1)\phi_2(x_2)$$
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This model implies $X_1$ and $X_2$ are independent, since:

$$ \Pr(X_1 = x_1, X_2 = x_2) = \Pr(X_1 = x_1) \Pr(X_2 = x_2) $$
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Two parameters (one per potential function) used to model three probabilities (4 possible outcomes): not a saturated model.
We can add a potential function to model the *pairwise interaction* between $X_1$ and $X_2$:

\[
\phi_{12}(x_1, x_2) = \begin{cases} 
  c & \text{if } x_1 = s_1 \land x_2 = s_1 \\
  d & \text{if } x_1 = s_2 \land x_2 = s_1 \\
  e & \text{if } x_1 = s_1 \land x_2 = s_2 \\
  f & \text{if } x_1 = s_2 \land x_2 = s_2 
\end{cases}
\]
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f & \text{if } x_1 = s_2 \land x_2 = s_2 
\end{cases}
\]

To obtain:

\[
\Pr(X_1 = x_1, X_2 = x_2) \propto \phi_1(x_1)\phi_2(x_2)\phi_{12}(x_1, x_2)
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\phi_{12}(x_1, x_2) = \begin{cases} 
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\end{cases}
$$

To obtain:

$$
\Pr(X_1 = x_1, X_2 = x_2) \propto \phi_1(x_1) \phi_2(x_2) \phi_{12}(x_1, x_2)
$$
Let $X^\top = [X_1 \ X_2 \ X_3]$ with realization $x$. No interaction between $X_1$ and $X_3$, $\phi_{13}(x_1, x_3) = 1 \ \forall x_1, x_3$, gives:

$$\Pr(X = x) \propto \phi_1(x_1) \phi_2(x_2) \phi_3(x_3) \phi_{12}(x_1, x_2) \phi_{23}(x_2, x_3)$$
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\Pr (X = x) \propto \phi_1(x_1)\phi_2(x_2)\phi_3(x_3)\phi_{12}(x_1, x_2)\phi_{23}(x_2, x_3)
$$

$X_1$ and $X_3$ are \textit{conditionally} independent:

$$
\Pr (X_{- (2)} = x_{- (2)} \mid X_2 = x_2) \propto \phi_1(x_1)\phi_{12}(x_1, x_2)\phi_3(x_3)\phi_{23}(x_2, x_3)
\propto \phi_1^*(x_1)\phi_3^*(x_3)
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$$\propto \phi^*_1(x_1)\phi^*_3(x_3)$$

But not \textit{marginally} independent:

$$\Pr(X_{-(2)} = x_{-(2)}) \propto \sum_{x_2} \phi_1(x_1)\phi_2(x_2)\phi_3(x_3)\phi_{12}(x_1, x_2)\phi_{23}(x_2, x_3)$$
Ising Model
Pairwise Markov Random Field:

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Pairwise Markov Random Field:

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Now encode \( S_1 = 1 \) and \( S_2 = -1 \), we can define without loss of information (in binary setting):

\[
\ln \phi_i (x_i) = \tau_i x_i \\
\ln \phi_{ij} (x_i, x_j) = \omega_{ij} x_i x_j
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Pairwise Markov Random Field:

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\[ \ln \phi_i (x_i) = \tau_i x_i \]
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This gives the Ising Model:

\[ \Pr (X = x) \propto \exp \left( \sum_i \tau_i x_i + \sum_{<ij>} \omega_{ij} x_i x_j \right) \]

in which \( \tau_i \) encodes the potential of \( X_i \) to be in state 1 or \(-1\) and \( \omega_{ij} \) encodes the strength of connection between \( X_i \) and \( X_j \).
Estimating an Ising model

- Due to the intractable normalizing constant, standard methods for estimating an Ising model (e.g., maximum likelihood) are not practical.
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\Pr \left( X_i = X_i \mid X_{-(i)} = x_{-(i)} \right) \propto \exp \left( \left( \tau_i + \sum_{j,j \neq i} \omega_{ij} x_j \right) x_i \right)
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- This is a *multiple logistic regression* model!
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- This is a *multiple logistic regression* model!

- The Ising model can thus be estimating by performing several multiple logistic regressions.
\[
\Pr(X_1 = 1) \propto \exp(\tau_1 + \omega_{12}x_2 + \omega_{14}x_4)
\]
\[ \Pr(X_2 = 1) \propto \exp(\tau_2 + \omega_{12}x_1 + \omega_{23}x_3) \]
\[
\Pr(X_3 = 1) \propto \exp(\tau_3 + \omega_{23}X_2 + \omega_{34}X_4)
\]
\[
\Pr(X_4 = 1) \propto \exp(\tau_4 + \omega_{14}x_1 + \omega_{34}x_3)
\]
Estimating an Ising model

Multivariate estimation options:

- Optimize the *pseudolikelihood*
  \[ \prod_i \Pr(X_i = X_i \mid X_{-i} = x_{-i}) \]
- Phrase the model as a loglinear model and use ML estimation
Estimating an Ising model

Multivariate estimation options:

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Methods for choosing which edges to include:

- Model selection
- Significance thresholding
- LASSO regularization
The Ising Model & Psychometrics

- The Ising model can be shown to be mathematically equivalent to a multidimensional IRT model.

- Rank-1 clusters in the network correspond to latent variables in the MIRT model

- This equivalence allows for re-interpretation of MIRT models and network models alike
Adding (arbitrary) variance potential function \( \ln \phi_{ii}(x_i) = \omega_{ii} x_i^2 \), we can write the Ising model as:

\[
\text{Pr}(X = x) \propto \exp \left( \tau^T x + \frac{1}{2} x^T \Omega x \right)
\]
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We can arbitrarily set the diagonal such that \( \Omega \succ 0 \), allowing us to take the eigenvalue decomposition:

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\Omega = Q\Lambda Q^T,
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Now, reparameterize $\tau_i = -\delta_i$ and $-2\sqrt{\frac{\lambda_j}{2}}q_{ij} = \alpha_{ij}$ to obtain:
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Now, reparameterize \( \tau_i = -\delta_i \) and \(-2\sqrt{\lambda_i / 2} q_{ij} = \alpha_{ij}\) to obtain:

\[
\Pr(X = x) = \int_{-\infty}^{\infty} f(\theta) \Pr(X = x \mid \Theta = \theta) \, d\theta
\]

With:

\[
\Pr(X_i = x_i \mid \Theta = \theta) = \frac{\exp \left( x_i (\alpha_i^T \theta - \delta_i) \right)}{\sum_{x_i} \exp \left( x_i (\alpha_i^T \theta - \delta_i) \right)}
\]

\[
\Theta \mid X = x \sim N \left( \pm \frac{1}{2} A^T x, \sqrt{\frac{1}{2} I} \right)
\]
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Gaussian Graphical Model
Now assume $X_i \in \mathbb{R}$ $\forall i$ and the log of all potential functions are *linear*, and include variance potential function $\phi_{ii}(x_i)$:

\[
\begin{align*}
\ln \phi_i(x_i) &= \tau_i x_i \\
\ln \phi_{ij}(x_i, x_j) &= -\kappa_{ij} x_i x_j \\
\ln \phi_{ii}(x_i) &= -\kappa_{ii} x_i^2
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Now assume \( X_i \in \mathbb{R} \ \forall i \) and the log of all potential functions are \textit{linear}, and include variance potential function \( \phi_{ii}(x_i) \):

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We obtain:

\[
\Pr(X = x) \propto \exp \left( \tau^\top x - \frac{1}{2} x^\top K x \right)
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\]

We obtain:

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\]

Now let \( \Sigma = K^{-1} \) and \( \mu = \Sigma \tau \):

\[
\Pr (X = x) \propto \exp \left( -\frac{1}{2} (x - \mu)^\top \Sigma^{-1} (x - \mu) \right)
\]

Which implies \( X \sim N(\mu, \Sigma) \)!
The Gaussian Graphical Model (GGM)

The precision matrix $K = \Sigma^{-1}$ encodes a network structure! Furthermore, this matrix can be standardized to *partial correlation coefficients*:

$$\text{Cor} \left( X_i, X_j \mid X_{- (i,j)} \right) = -\frac{K_{ij}}{\sqrt{K_{ii} K_{jj}}} = \omega_{ij}$$
The Gaussian Graphical Model (GGM)

The precision matrix $\mathbf{K} = \mathbf{\Sigma}^{-1}$ encodes a network structure! Furthermore, this matrix can be standardized to partial correlation coefficients:

$$\text{Cor} \left( X_i, X_j \mid X_{-(i,j)} \right) = \frac{-\kappa_{ij}}{\sqrt{\kappa_{ii} \kappa_{jj}}} = \omega_{ij}$$

Combining this information, we can form a psychometric model:

$$\mathbf{\Sigma} = \Delta (I - \Omega)^{-1} \Delta$$

- $\Delta$ is a diagonal scaling matrix
- $\Omega$ is a symmetrical matrix with 0 on the diagonal and partial correlation coefficients on offdiagonal elements
GGM estimation

- The GGM can be fitted similarly to SEM models, allowing for model search strategies
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- The conditional distribution of a GGM is a *multiple regression model*, which allows for nodewise estimation similar to Ising model estimation.
  - Edge selection via significance thresholding or regularization.
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GGM estimation

- The GGM can be fitted similarly to SEM models, allowing for model search strategies
- The conditional distribution of a GGM is a *multiple regression model*, which allows for nodewise estimation similar to Ising model estimation
  - Edge selection via significance thresholding or regularization
- The graphical LASSO is a fast way to obtain a range of GGM models to choose the best model from
- Bayesian estimation methods are also promising
**Agreeableness**
- A1: Am indifferent to the feelings of others.
- A2: Inquire about others’ well-being.
- A3: Know how to comfort others.
- A4: Love children.
- A5: Make people feel at ease.

**Conscientiousness**
- C1: Am exacting in my work.
- C2: Continue until everything is perfect.
- C3: Do things according to a plan.
- C4: Do things in a half-way manner.
- C5: Waste my time.

**Extraversion**
- E1: Don’t talk a lot.
- E2: Find it difficult to approach others.
- E3: Know how to captivate people.
- E4: Make friends easily.
- E5: Take charge.

**Neuroticism**
- N1: Get angry easily.
- N2: Get irritated easily.
- N3: Have frequent mood swings.
- N4: Often feel blue.
- N5: Panic easily.

**Openness**
- O1: Am full of ideas.
- O2: Avoid difficult reading material.
- O3: Carry the conversation to a higher level.
- O4: Spend time reflecting on things.
- O5: Will not probe deeply into a subject.
SEM and GGM

Both models imply a variance-covariance matrix $\Sigma$, aimed to closely resemble the sample variance-covariance matrix $S$ with positive degrees of freedom.
• MRF is uniquely identified and well parameterized
• MRF allows for exploratory hypothesis-generating insight in possible causal structures
Network models and SEM can be combined:

Time-series
Graphical Vector Auto-regression (VAR)

\[ X_t \mid x_{t-1} \sim N(Bx_{t-1}, \Theta) \]

- Variables assumed centered
- \( B \) encodes the *temporal network*
  - Temporal prediction
- \( \Theta^{-1} \) encodes the *contemporaneous network*
  - GGM
- Graphical VAR model
Estimation

- Multivariate multiple regression on lagged variables
- Edge selection via significance thresholding, model selection (LNM) or LASSO regularization
- Multi-level estimation allows for estimation on $N > 1$ datasets, but is more complicated
  - Two-step multi-level VAR using `mlVAR` R package
  - Bayesian estimation using `Mplus 8`
Estimation

- Multivariate multiple regression on lagged variables
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Important assumptions

- Stationarity
  - Means
  - Network structure

- Equidistant measurements
• Contemporaneous network: Partial correlations given $t - 1$
• Temporal network: regression coefficients between $t - 1$ and $t$

- Contemporaneous network: Partial correlations given \( t - 1 \)
- Temporal network: regression coefficients between \( t - 1 \) and \( t \)
- Between-subjects network: Partial correlations between means

Theory Formation
Slides by Julian Burger

Based on master-thesis project at the Amsterdam Institute for Advanced Studies

Prospected PhD student 2019 - 2023

Work together with Rick Quax and Don Robinaugh
Negative Emotionality

Regulation: Avoidance
Negative Emotionality Regulation: Avoidance

Stressor

- Fast change +/- days
- Slow change +/- weeks
Negative Emotionality
Regulation: Avoidance
Tolerance
Stressor fast change +/-days slow change +/-weeks
Negative Emotionality Regulation: Avoidance Tolerance Evaluation

Stressor

fast change +/-days

slow change +/-weeks

Evaluation

Tolerance

Regulation: Avoidance

Negative Emotionality
Negative Emotionality:

\[
\frac{dNE}{dt} = (A \times Str. - B - (C - D \times Tol.) \times Av.) \times NE \times (1 - NE)
\]
**Negative Emotionality:**

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Negative Emotionality
Regulation: Avoidance
Tolerance
Evaluation

Stressor

fast change +/-days
slow change +/-weeks

A B
C DEF
G
H
IJ
K
L
M

Evaluation

Regulation: Avoidance

Tolerance
Fast Change Equations

Negative Emotionality:
\[ \frac{dNE}{dt} = \left( (A \times Str.) - B - (C - D \times Tol.) \times Av. \right) \times NE \times (1 - NE) \]

Regulation (Avoidance):
\[ \frac{dAv.}{dt} = \left( (E + F \times Ev.) \times NE - G \times Av. \right) \times Av. \times (1 - Av.) \]

Scaling: 0 - 1
Negative Emotionality
Regulation: Avoidance
Tolerance Evaluation
Stressor fast change +/- days
slow change +/- weeks
A B
C D E F
G H I J K L M
**Tolerance:**
\[
\frac{dTol.}{dt} = \frac{(H \times Av.* (1 - Tol.) - I \times Tol.)}{7}
\]

**Stressor:**
\[
\frac{dStr.}{dt} = \frac{(J \times Av.* (1 - Str.) - K \times Str.)}{7}
\]

**Evaluation:**
\[
\frac{dEv.}{dt} = \frac{(Ev.* (1 - Ev.*) \times C - L \times Ev.)}{7}
\]
Incorporating random Mood Swings and Stressors

Scenario 1: No Intervention
**Intervention 1: Reduce Substance Use at t = 4000**

**Scenario 2: Behavioral Therapy**

- **Negative Emotionality**: Avoidance
- **Tolerance**: Stressor

---

**Graphs**

- Positive Emotionality over time
- Avoidance: Substance Use over time
- Tolerance over time
- Stressor over time

---

**Key Points**

- Intervention 1: Reduce Substance Use at t = 4000
- Negative Emotionality: Avoidance
- Tolerance: Stressor

---

**Scenario 2**

- Behavioral Therapy
- Negative Emotionality
- Regulation: Avoidance
- Evaluation
- Tolerance

---

**Graphs**

- Time-series showing changes over days and weeks
Intervention 2: Cognitive Therapy from $t = 4000$

Scenario 3: Cognitive Therapy

- **Negative Emotionality**
- **Avoidance: Substance Use**
- **Tolerance**
- **Stressor**

Evaluation

Regulation: Avoidance

fast change +/-days

slow change +/-weeks
CBT at $t = 4000$

Scenario 4: CBT

- **Negative Emotionality**
  - Time: 0 to 10000
  - Y-axis: 0 to 0.8
  - Graph shows upward trend followed by a decrease.

- **Avoidance: Substance Use**
  - Time: 0 to 10000
  - Y-axis: 0 to 0.8
  - Graph shows an initial increase followed by a decrease.

- **Tolerance**
  - Time: 0 to 10000
  - Y-axis: 0 to 0.4
  - Graph shows a steady increase.

- **Stressor**
  - Time: 0 to 10000
  - Y-axis: 0 to 0.4
  - Graph shows a fluctuating pattern.

- **Evaluation**
  - Connected to Stressor and Negative Emotionality.

- **Negative Emotionality**
  - Connected to Evaluation and Tolerance.

- **Regulation: Avoidance**
  - Connected to Stressor and Evaluation.

- **Tolerance**
  - Connected to Evaluation and Negative Emotionality.

**Stressor**
- Fast change +/- days
- Slow change +/- weeks
Conclusion
Current state of Network Psychometrics

- Applied in over 100 empirical papers
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- Many software packages available
  - e.g., qgraph, bootnet, lvnet, graphicalVAR, mlVAR, IsingSampler, IsingFit, mgm, NetworkToolbox, JASP
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- Popular Facebook group!
  - Psychological Dynamics
Towards mathematical models

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  - Networks are estimated without any theory
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  - Build networks from the ground up, based on theory
Towards mathematical models

- Estimating network models is currently agnostic
  - Networks are estimated without any theory
- Two ways to incorporate theory (e.g., clinical expertise):
  - Priors in Bayesian analysis
  - Build networks from the ground up, based on theory
- Dynamical systems modeling of psychological phenomena is promising
Thank you for your attention!

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