Estimating network-mediated causal effects via spectral embeddings

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Abstract

We consider the task of mediation analysis for network data, and present a model in which mediation occurs in a latent embedding space. Under this model, node-level interventions have causal effects on nodal outcomes, and these effects can be partitioned into a direct effect independent of the network, and an indirect effect induced by homophily.

Motivating example: smoking in adolescent social networks

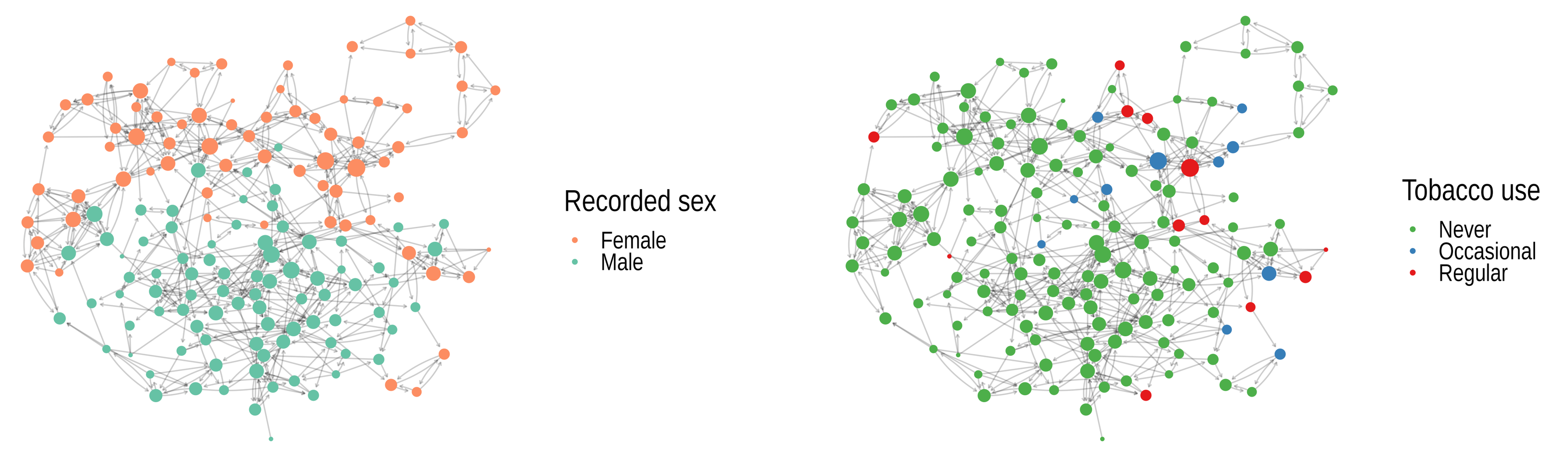

Figure 1. Directed friendships in a secondary school in Glasgow, reported in the Teenage Friends and Lifestyle Study (wave 1). Each node represents one student.

Notation & inferential targets

We assume we have a (symmetric) network with nodes $1, \ldots, n$.

Network adjacency matrix	A	$\in \mathbb{R}^{n \times n}$
Edge $i \sim j$	A_{ij}	$\in \mathbb{R}$
Treatment	T_i	$\in \{0,1\}$
Outcome	Y_i	$\in \mathbb{R}$
Confounders	$C_{i\cdot}$	$\in \mathbb{R}^p$
Friend group (latent)	$X_{i\cdot}$	$\in \mathbb{R}^d$

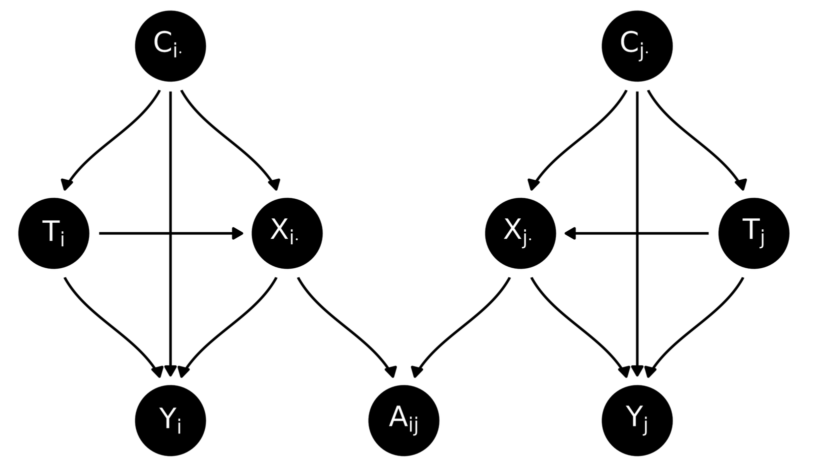

Figure 2. A directed acyclic graph (DAG) representing the causal pathways in a network with homophilous mediation, for node a network with two nodes called i and j.

We are interested in the causal effect of T_i on Y_i as mediated by the latent position $X_{i\cdot}$. More precisely, we want to estimate the *natural direct effect* and the *natural indirect effect*

$$\Psi_{\mathrm{nde}}(t, t^*) = \mathbb{E}[Y_i(t, X_{i\cdot}(t^*)) - Y_i(t^*, X_{i\cdot}(t^*))]$$
$$\Psi_{\mathrm{nie}}(t, t^*) = \mathbb{E}[Y_i(t, X_{i\cdot}(t)) - Y_i(t, X_{i\cdot}(t^*))]$$

Semi-parametric network model

Let $A \in \mathbb{R}^{n \times n}$ be a random matrix, such as the adjacency matrix of an undirected graph. Let $P = \mathbb{E}[A \mid X] = XX^T$ be the expectation of A conditional on $X \in \mathbb{R}^{n \times d}$, which has independent and identically distributed rows $X_{1\cdot}, \ldots, X_{n\cdot}$. That is, P has $\operatorname{rank}(P) = d$ with eigenvalues $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_d > 0 = \lambda_{d+1} = \cdots = \lambda_n$. Conditional on X, the upper-triangular elements of $A - P$ are independent (ν_n, b_n)-sub-gamma random variables.

Examples: (degree-corrected, mixed-membership) stochastic blockmodels, overlapping blockmodels, (weighted, noisily-observed) random dot product graphs, LDA, factor models, etc

The outcome regression functional is linear in $T_i, C_{i\cdot}$, and $X_{i\cdot}$ and the mediator regression functional is linear in $T_i, C_{i\cdot}$, and $T_i \cdot C_{i\cdot}$:

$$\underbrace{\mathbb{E}[Y_i \mid T_i, C_{i\cdot}, X_{i\cdot}]}_{\mathbb{R}} = \underbrace{\beta_0}_{\mathbb{R}} + \underbrace{T_i}_{\{0,1\}} \underbrace{\beta_{\mathrm{t}}}_{\mathbb{R}} + \underbrace{C_{i\cdot}}_{\mathbb{R}^{1\times p}} \underbrace{\beta_{\mathrm{c}}}_{\mathbb{R}^p} + \underbrace{X_{i\cdot}}_{\mathbb{R}^{1\times d}} \underbrace{\beta_{\mathrm{x}}}_{\mathbb{R}^d}, \qquad \text{(outcome model)}$$

$$\underbrace{\mathbb{E}[X_{i\cdot} \mid T_i, C_{i\cdot}]}_{\mathbb{R}^{1\times d}} = \underbrace{\theta_0}_{\mathbb{R}^{1\times d}} + \underbrace{T_i}_{\{0,1\}} \underbrace{\theta_{\mathrm{t}}}_{\mathbb{R}^{1\times d}} + \underbrace{C_{i\cdot}}_{\mathbb{R}^{1\times p}} \underbrace{\Theta_{\mathrm{c}}}_{\mathbb{R}^{p\times d}} + \underbrace{T_i}_{\{0,1\}} \underbrace{C_{i\cdot}}_{\mathbb{R}^{1\times p}} \underbrace{\Theta_{\mathrm{tc}}}_{\mathbb{R}^{p\times d}}. \qquad \text{(mediator model)}$$

Under these moment assumptions, and DAG of Figure 2, letting μ_c denote the mean of $C_{i\cdot}$, we have the following identification result:

$$\Psi_{\mathrm{nde}}(t, t^*) = (t - t^*)\, \beta_{\mathrm{t}}, \quad \text{and}$$
$$\Psi_{\mathrm{nie}}(t, t^*) = (t - t^*)\, \theta_{\mathrm{t}}\, \beta_{\mathrm{x}} + (t - t^*)\, \mu_c\, \Theta_{\mathrm{tc}}\, \beta_{\mathrm{x}}.$$

Estimation challenge: friend groups X unknown!

The *adjacency spectral embedding* (ASE) of A is well-known estimate of X under the network model described above, defined as

$$\widehat{X} = \widehat{U}\widehat{S}^{1/2} \in \mathbb{R}^{n \times d},$$

where $\widehat{U}\widehat{S}\widehat{U}^T$ is the rank-d truncated singular value decomposition of A. Under a suitably well-behaved model, if d is correctly specified, there is an orthogonal matrix Q such that

$$\max_{i \in [n]} \left\| \widehat{X}_{i\cdot} - X_{i\cdot} Q \right\| = o_p(1).$$

Let $\widehat{D} = \begin{bmatrix} 1 & T & C & \widehat{X} \end{bmatrix} \in \mathbb{R}^{n \times (2+p+d)}$ and $L = \begin{bmatrix} 1 & T & C & T \cdot C \end{bmatrix} \in \mathbb{R}^{n \times (2p+2)}$. We estimate β_{w}, β_{x} and Θ via ordinary least squares as follows

$$\begin{bmatrix} \widehat{\beta}_{\mathrm{w}} \\ \widehat{\beta}_{\mathrm{x}} \end{bmatrix} = \left(\widehat{D}^T \widehat{D}\right)^{-1} \widehat{D}^T Y \quad \text{and} \quad \widehat{\Theta} = \left(L^T L\right)^{-1} L^T \widehat{X}.$$

To estimate Ψ_{nde} and Ψ_{nie}, let $\widehat{\mu}_c$ be the sample mean of $C_{i\cdot}$ and combine regression coefficients from the network regression models

$$\widehat{\Psi}_{\mathrm{cde}} = \widehat{\Psi}_{\mathrm{nde}} = (t - t^*)\, \widehat{\beta}_{\mathrm{t}} \quad \text{and} \quad \widehat{\Psi}_{\mathrm{nie}} = (t - t^*)\, \widehat{\theta}_{\mathrm{t}}\, \widehat{\beta}_{\mathrm{x}} + (t - t^*) \cdot \widehat{\mu}_c \cdot \widehat{\Theta}_{\mathrm{tc}}\, \widehat{\beta}_{\mathrm{x}},$$

Theory

Under a suitable network model and moment bounds on the regression errors, there exists a sequence of orthogonal matrices $\{Q_n\}_{n=1}^{\infty}$ such that

$$\sqrt{n}\, \widehat{\Sigma}_{\mathrm{vec}(\Theta)}^{-1/2} \left(\mathrm{vec}\left(\widehat{\Theta}\, Q_n^T\right) - \mathrm{vec}(\Theta) \right) \to \mathcal{N}(0, I_{pd}), \text{ and}$$
$$\sqrt{n}\, \widehat{\Sigma}_{\beta}^{-1/2} \begin{pmatrix} \widehat{\beta}_{\mathrm{w}} - \beta_{\mathrm{w}} \\ Q_n \widehat{\beta}_{\mathrm{x}} - \beta_{\mathrm{x}} \end{pmatrix} \to \mathcal{N}(0, I_d).$$

Further,

$$\sqrt{n\, \widehat{\sigma}^2_{\mathrm{nde}}} \left(\widehat{\Psi}_{\mathrm{nde}} - \Psi_{\mathrm{nde}} \right) \to \mathcal{N}(0,1), \qquad \text{and}$$
$$\sqrt{n\, \widehat{\sigma}^2_{\mathrm{nie}}} \left(\widehat{\Psi}_{\mathrm{nie}} - \Psi_{\mathrm{nie}} \right) \to \mathcal{N}(0,1),$$

where $\widehat{\sigma}^2_{\mathrm{nde}}$ and $\widehat{\sigma}^2_{\mathrm{nie}}$ are derived via the Delta method.

Results applied to Glasgow data

- Estimated effects are adjusted for possible confounding by age and church attendance.
- Estimated effects vary with the chosen dimension d of the latent space
- Over-specifying d is typically okay, but under-specifying d leads to a failure to capture social structure in X
- Once we capture enough social structure in X, we see a significant indirect social effect that leads adolescent girls to smoke more

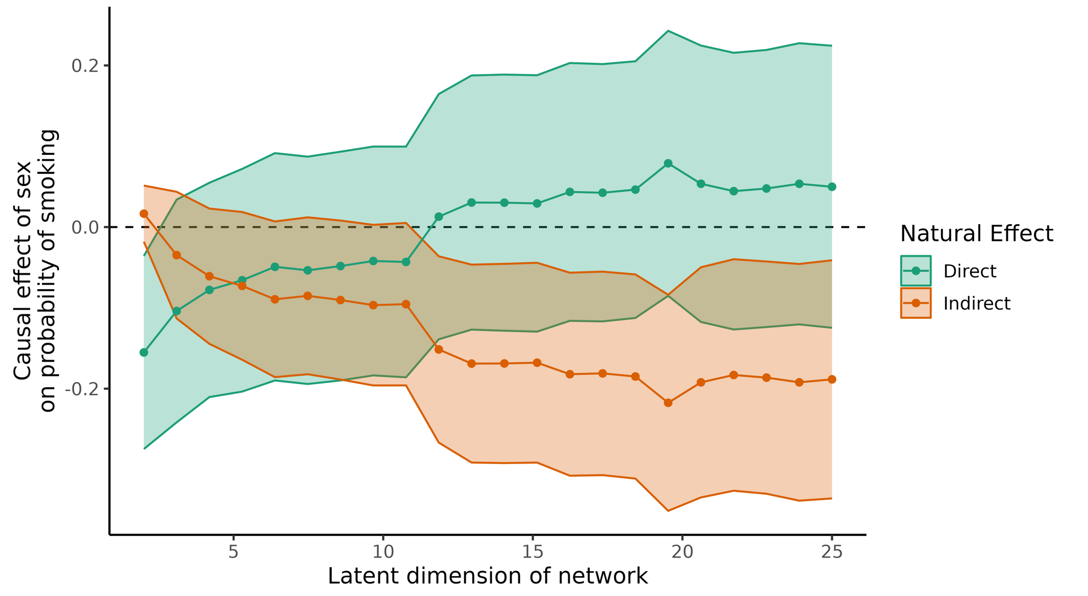

Figure 3. Estimated direct and indirect effects of sex on tobacco usage in the Glasgow social network. Positive values indicate a greater propensity for adolescent boys to smoke, negative effects a greater propensity for adolescent girls to smoke.

References

Hayes, Alex, Mark M. Fredrickson, and Keith Levin. "Estimating Network-Mediated Causal Effects via Spectral Embeddings." arXiv, April 14, 2023. `http://arxiv.org/abs/2212.12041`.