Estimating Causal Effects Using Proxy Interference Networks

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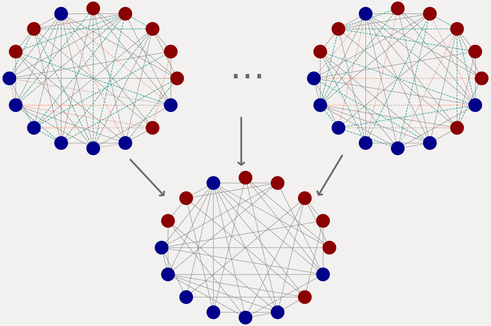

Background

- **Causal Inference**. Estimate the effect of treatment on an outcome.
- **Interference**. Treatment of one unit affect the outcomes of others.
- Treatments spreads through a network.
  - Nodes: units; Edges: magntiude of pairwise interfernce.

Background

- **Causal Inference.** Estimate the effect of treatment on an outcome.
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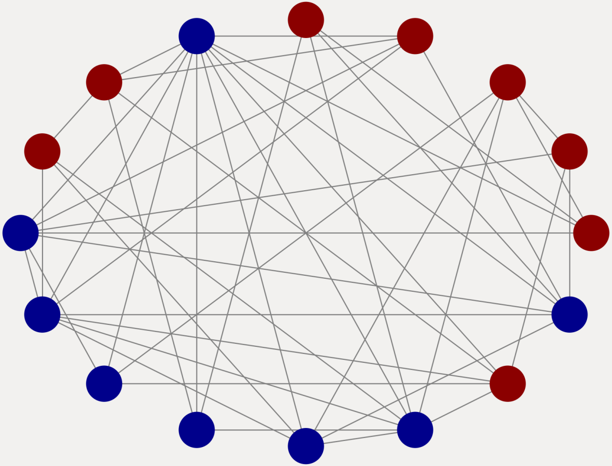
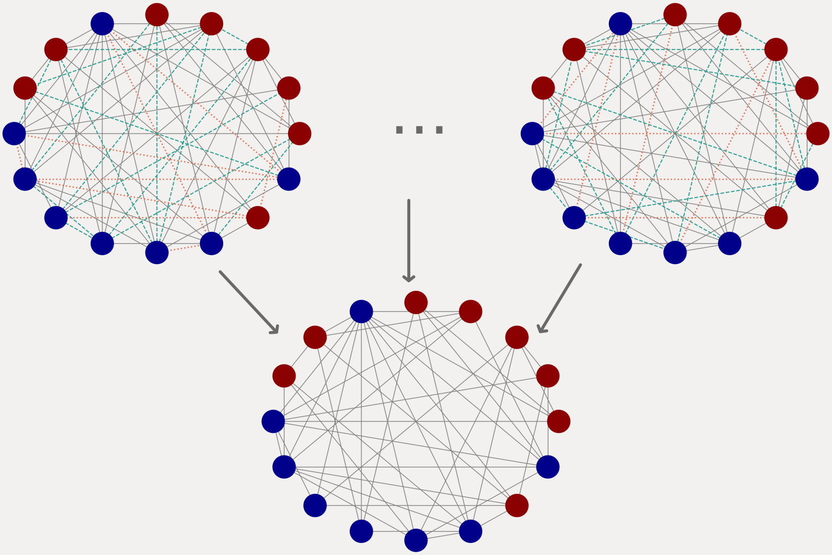
- Examples:
  - *Social networks.* Transmission of information, behavior, encouragements, etc.
  - *Epidemiology.* Mitigating spread of infectious diseases or addictive drugs.
  - A/B testing in marketplaces.



The Challenge

- Accurately measuring social networks is challenging.
- We observe only proxy measurements of the true network.
  - Measurements error.
  - Multiple sources of data.
  - Multilayer networks.
- True network remains latent.

How can we estimate causal effects using proxy networks?



Illustrative Example – Paluck et al. (2016)

- Field experiement in 56 middle-schools.
- Study how anti-conflict education spread through social networks.
- Measured social networks using self-reported friendships.
  - Bi-layer networks: frequently interacted and best friends.
  - Measured at pre- and post-intervention period.

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- Field experiement in 56 middle-schools.
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- Measured social networks using self-reported friendships.
  - Bi-layer networks: frequently interacted and best friends.
  - Measured at pre- and post-intervention period.
- Which of the networks, if any, is the true network?
- **Objective:** Estimate the intervention effects using the proxy networks.

Formal Framework

MATH HERE

Structural Causal Model

SCM and relevant DAG or equations here.

Plate-notation graph of the model (?)

Bayesian Inference

Bayesian approach for estimation and inference. Posterior composed of discrete and continuous parameters. Give high-level details of sampling algos (cut-posterior and informed proposals).

Two figures: MAPE of estimated treatment effects and MAE of exposure mapping.

Results of Paluck et al. (2016) analysis.

Figures and Tables

Figure 1: Figure caption.

	Heading 1	Heading 2
Row 1	v_{11}	v_{12}
Row 2	v_{21}	v_{22}
Row 3	v_{31}	v_{32}

Table 1: Table caption.

Thanks for using **Focus**!

References

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Appendix

More math details.