Unintended Consequences in Network Interventions

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How should we organize people and information for innovation?

Research

Interorganizational networks known to affect innovation

Practice

Interventions that try to induce beneficial relationships often fail.

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Practice

Interventions that try to induce beneficial relationships often fail.

How should we design network interventions?

One reason for difficulty

Interdependence between network composition and structure

Endogenous networks tend to exhibit induced homophily Any new edge we changes both network properties

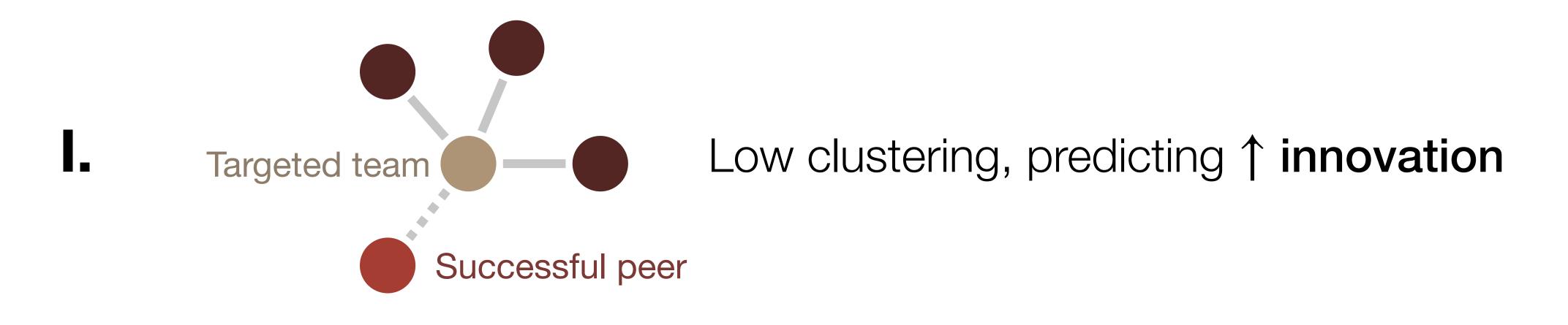
Interventions often designed to target either composition or structure

- I. Increasing connectivity across fragmented groups (healthcare, science)
- II. Inducing connections to peers with specific attributes (entrepreneurship, education)

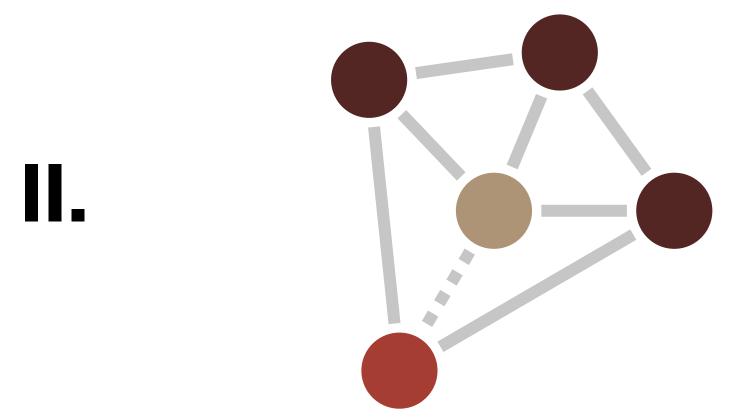
But both properties affect outcomes, opening a backdoor

Imagine two alternate worlds

Both treat the targeted team with a successful peer, predicting 1 innovation

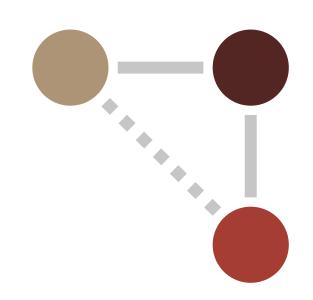






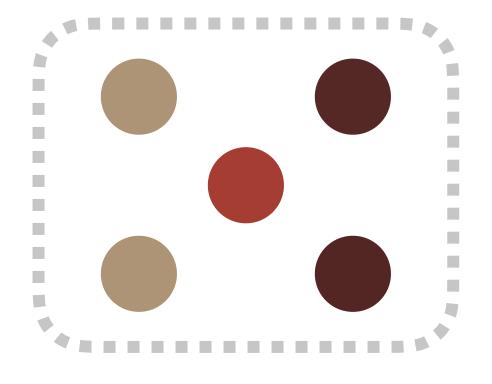
Dense clustering, predicting \$\psi\$ innovation

Families of network interventions



Local search through alters

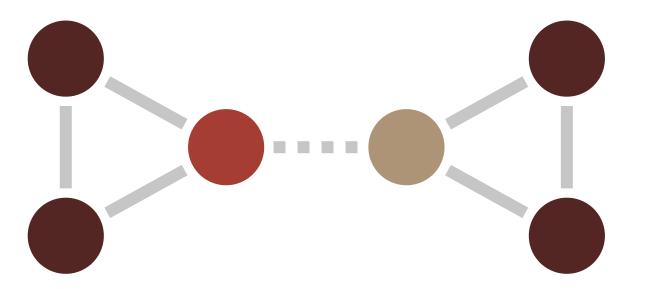
† Clustering
High Efficacy



Local search by colocation

Clustering

Medium Efficacy



Distant search multiple mechanisms

↓ Clustering Low Efficacy

Research Design

To understand how the design of network interventions affects their success

I. Estimate average causal effect of local networks on team innovation

Data: 10-year panel of iGEM teams

Treatment: 1 ≤ successful peer; local clustering coefficient

Outcome: Probability of successful innovation

Estimator: Exponential Random Graph-IPTW-Logit

II. Simulate effect of intervention under different initial conditions

Agent-Based Models of several common designs

Payoffs calculated using parameters from (I.)

Simulating network interventions

Begin with a small-world network (Newman-Watts) defined by

- 1. Number of nodes
- 2. Proportion of nodes with binary attribute $y_{t-1} = 1$
- 3. Degree of homophily
- 4. Characteristic path length
- 5. Global clustering coefficient
- 6. Set of nodes targeted for treatment

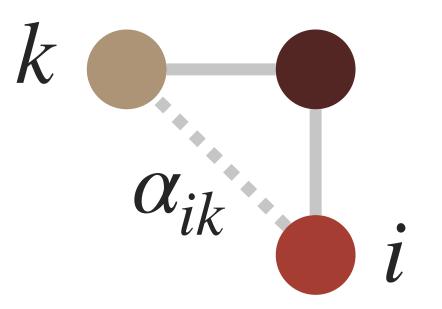
Interventions are probabilistic rules about how the network changes

Details on coming slides

Rule 1: Local search through alters

For each targeted node i,

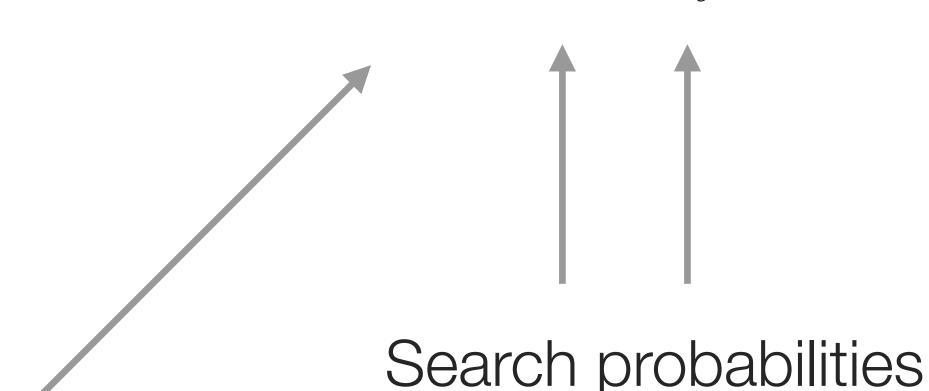
- 1. Select a candidate alter k with attribute $y_{k(t-1)=1}$ and no prior connection to i
- 2. If one exists, form an edge α_{ik} with p_1



Rule 2: Local search through colocation

Select a subset J' of nodes to colocate.

For each pair $ij \in J'$ form an edge α_{ij} with probability $p_2 \times q_i \times q_j$

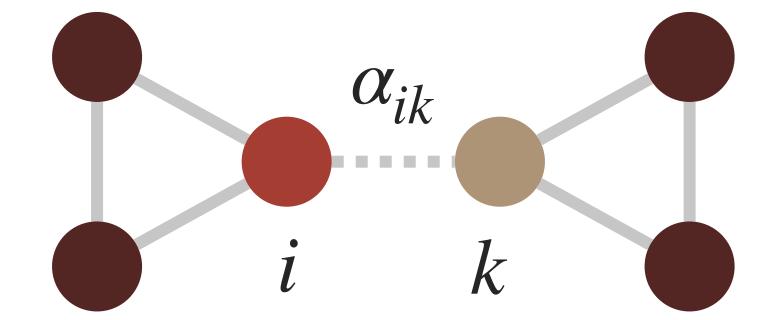


Ease of search and probability requests being accepted

$$q_i = \exp\left[-\sum_{j}^{J'} \alpha_{ij(t-1)}\right]$$

Rule 3: Distant search

For each targeted node i,



- 1. Select a candidate alter k with
 - Node attribute $y_k = 1$
 - No prior connection to i or any of their neighbors
- 2. If exists, form an edge $lpha_{ik}$ with probability p_3 :

$$p_1 > p_2 > p_3$$

Payoffs

Run each intervention 1,000 × for each set of initial conditions

Calculate node payoff from simulated statistics and empirical parameters

Within each intervention × condition

- 1. Variance across targeted nodes?
- 2. Heterogeneity based on initial node position?
- 3. Total average treatment effect
- 4. Variance of ATE across individuals

Across interventions × conditions

- 5. Which intervention should we choose under different decision rules (minimax, maximin, expected value)
- 6. Sensitivity to initial global conditions

A few open questions

- I. Is this validated by empirical evidence? Want to check predictions but few settings where we have intervention + node attributes + structural data
- II. How much should the network evolve post-intervention? tie decay, triadic closure, etc.

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