

# The Structure of Social Data

<http://www.stanford.edu/~jugander/mse334/>

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Stanford University  
9/22/2015

# Course outline

Week 1: Introduction and Overview

Week 2: Heavy-tailed distributions; Random graphs

Week 3: More graph models

Week 4: Graph centrality and ranking

Week 5: Ranking from comparisons; Friendship paradoxes

Week 6: Homophily, social influence, contagion

Week 7: Causal inference on networks

Week 8–9: Synthesis; dissecting complex papers

Week 10: Project presentations

# Practical components

Problem Set 1: Manipulating data (due 10/8)

Problem Set 2: Theory exercises (due 10/20)

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Problem Set 2: Theory exercises (due 10/20)

Reaction paper: (due 10/27)

Groups of 1–3. Skim some papers on the course homepage. Pick a paper to read carefully; pick a citation there–in, read it carefully.

**Prompt:** What are the weaknesses of the papers, and how could they be improved? What are some promising further research questions in the direction of the papers, and how could they be pursued?

10/27–11/3: Discussion meetings with me!

1 week after meeting: Project proposal

# Projects

Basic genres:

- An empirical evaluation of an algorithm, model, or measure on an interesting dataset.
- A theoretical project that considers an algorithm, model, or measure in the area of some course topic, and derives rigorous results about it.
- An extended, critical survey of one the course topics, going into significant depth and offering a novel perspective on the area.

**12/1:** Report due

**12/1 & 12/3:** In-class presentations

**Questions?**

# Learning outcomes

1. Students should develop a familiarity with relevant structural properties of empirical social networks, and how different graph models capture or don't capture these properties.
2. Students should be able to weigh advantages and disadvantages of different observational and experimental study designs that examine/test mechanisms in social systems.
3. Students should be able to employ structural measures for diverse ranking/predicting problems on graphs.
4. Students should be able to critically read research papers in the field to identify strengths and potential weaknesses, and to be able to design tests of potential weaknesses.

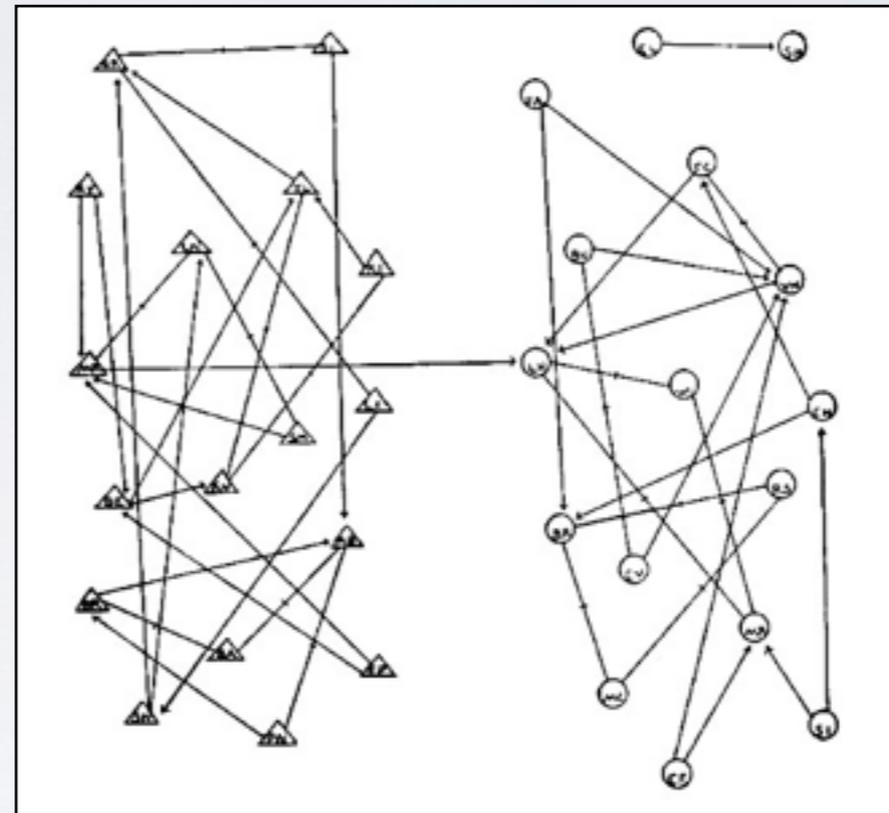
**Ready?**

# Social networks: mapping structure

## EMOTIONS MAPPED BY NEW GEOGRAPHY

Charts Seek to Portray the  
Psychological Currents of  
Human Relationships.

FIRST STUDIES EXHIBITED

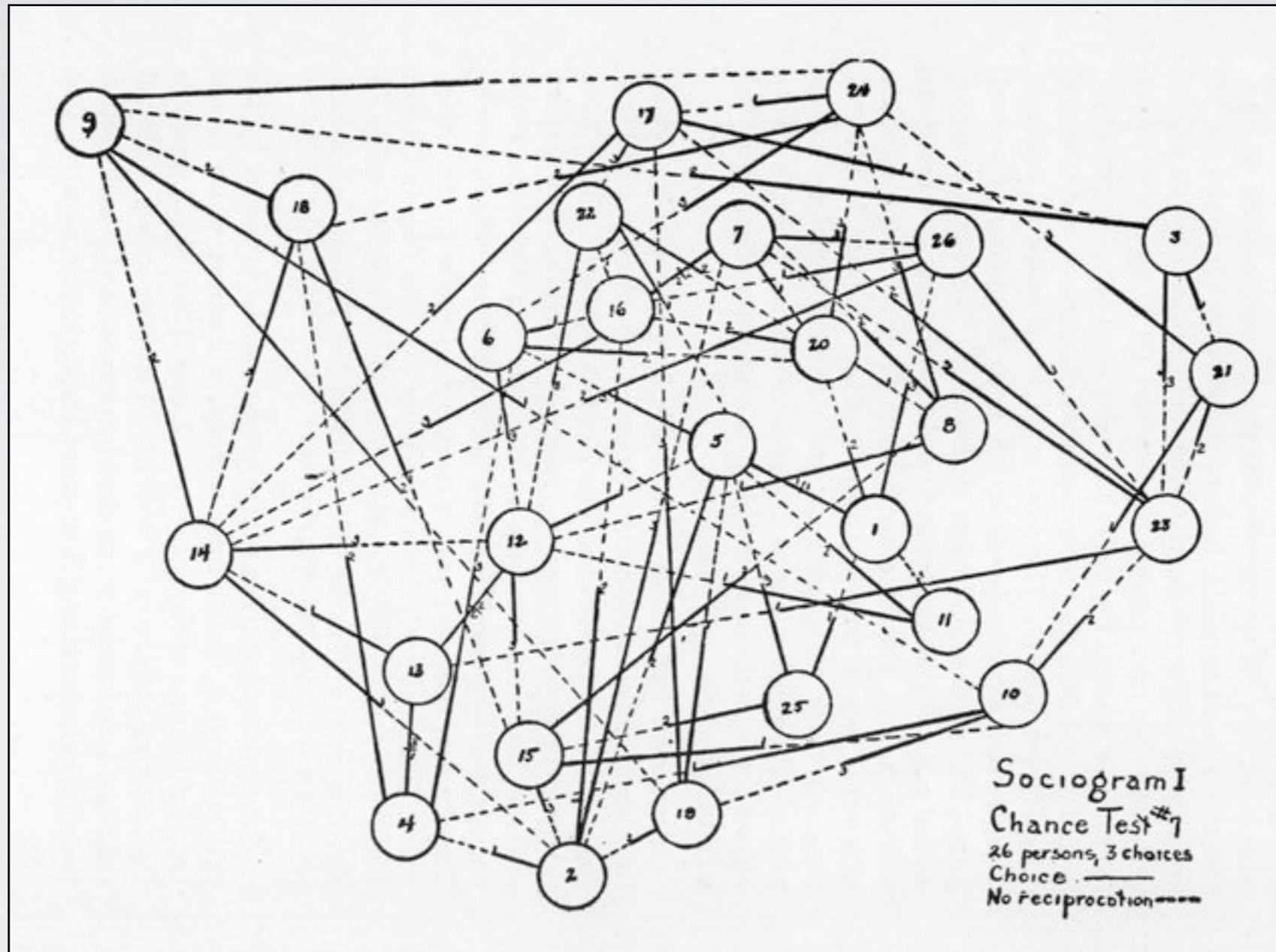


n=33

First “sociogram”: 8th grade students studying in proximity

- J Moreno (1934) “Who shall survive?: A new approach to the problem of human interrelations.”

# Social networks: mapping structure



Moreno's "chance sociogram": a random graph null model

- J Moreno (1934) "Who shall survive?: A new approach to the problem of human interrelations."

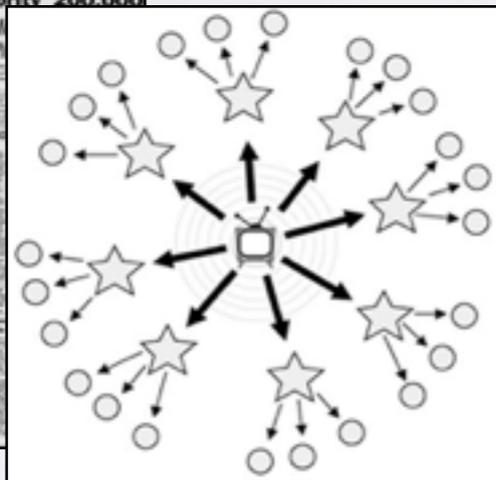
# The digital microscope



$n > 1,400,000,000$

# Processes on social networks

1940 election:  
two-step theory of  
opinion leaders



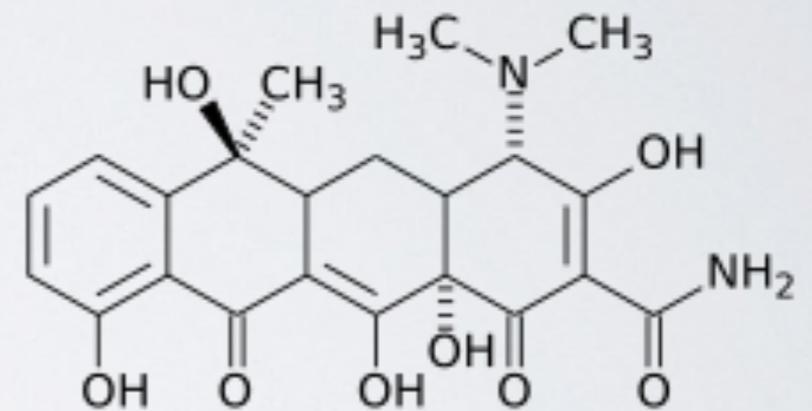
Lazarsfeld et al. '55  
Watts-Dodds '07

Hybrid seed corn



Ryan-Gross '43

Tetracycline



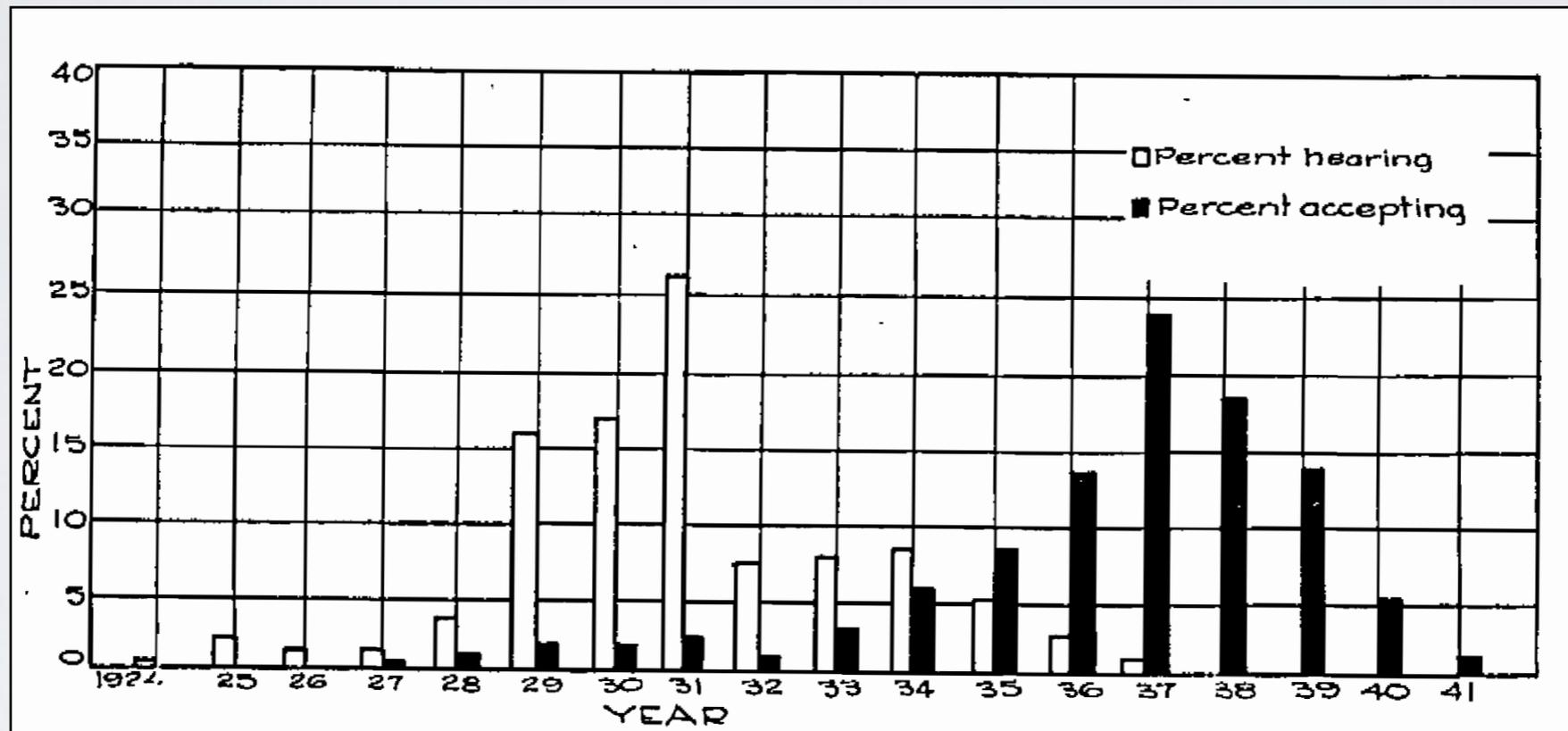
Coleman-Katz-Menzel '57

- B Ryan, N Gross (1943) "The diffusion of hybrid seed corn in two Iowa communities", Rural sociology.
- P Lazarsfeld; B Berelson, H Gaudet (1948) "The People's Choice. How the Voter Makes up His Mind in a Presidential Campaign".
- E Katz, P Lazarsfeld (1955) "Personal Influence, The part played by people in the flow of mass communications".
- E Katz (1957) "The Two-Step Flow of Communication: An Up-To-Date Report on an Hypothesis". Political Opinion Quarterly.
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# Processes on social networks

## Hybrid seed corn (Ryan-Gross):

5 stages: awareness, interest, evaluation, trial, adoption

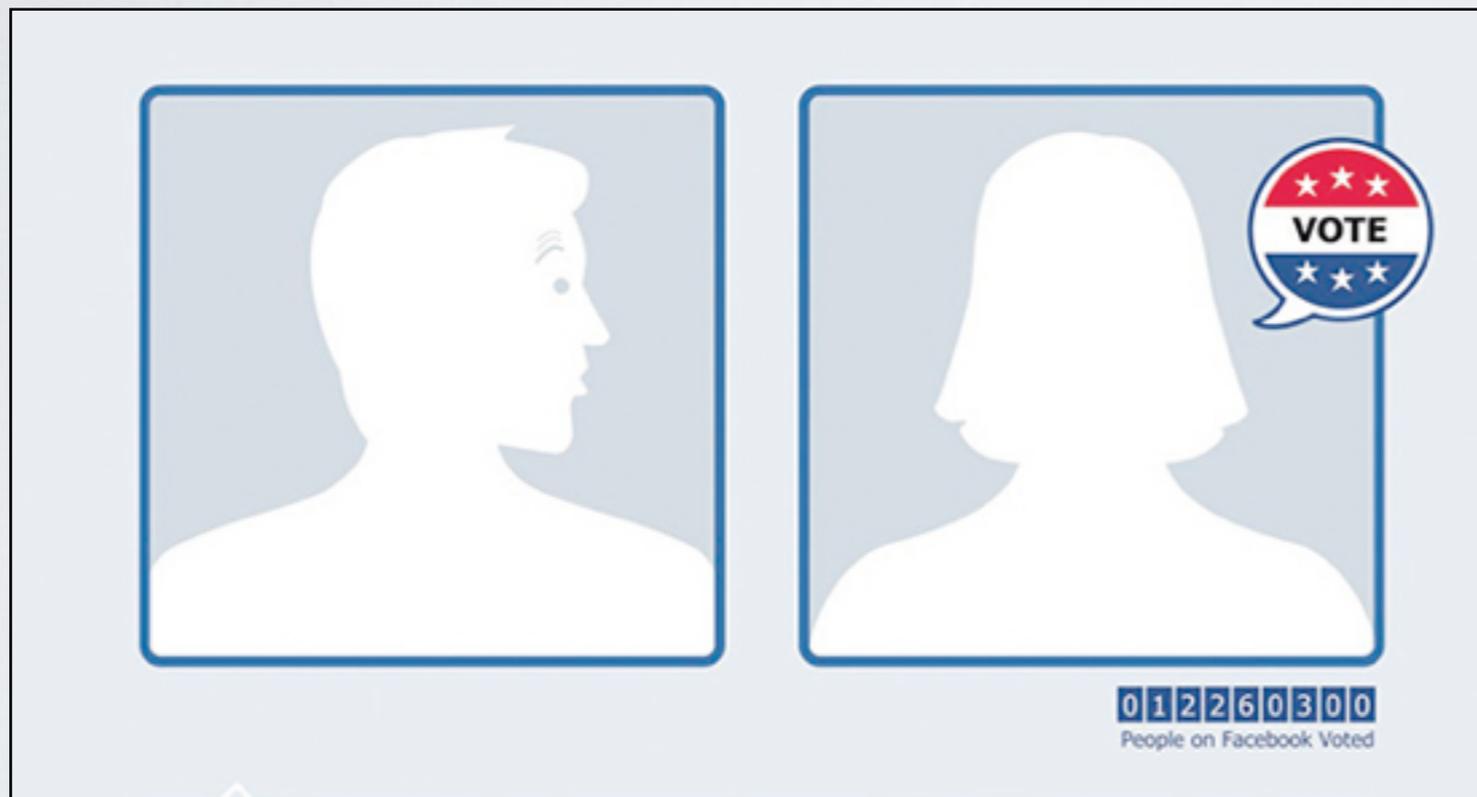


Survey of n=259 farmers

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# Digital experimental microscope

Massive experiments to test theories of social processes on large-scale networks.



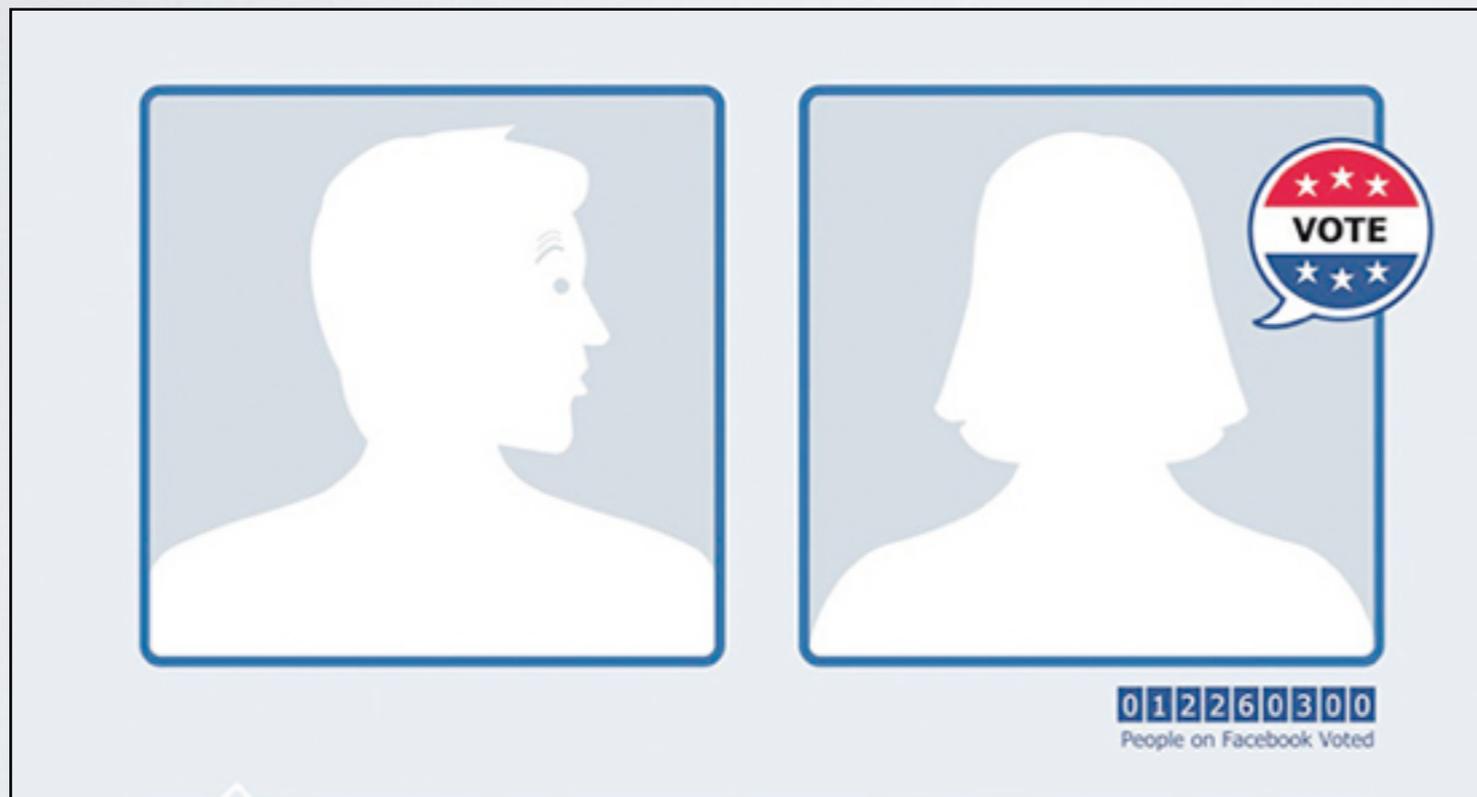
Experiment on  $n=61,000,000$  Facebook users

Not just FB: Telenor service experiment ( $n=46,000$ ), LinkedIn, others.

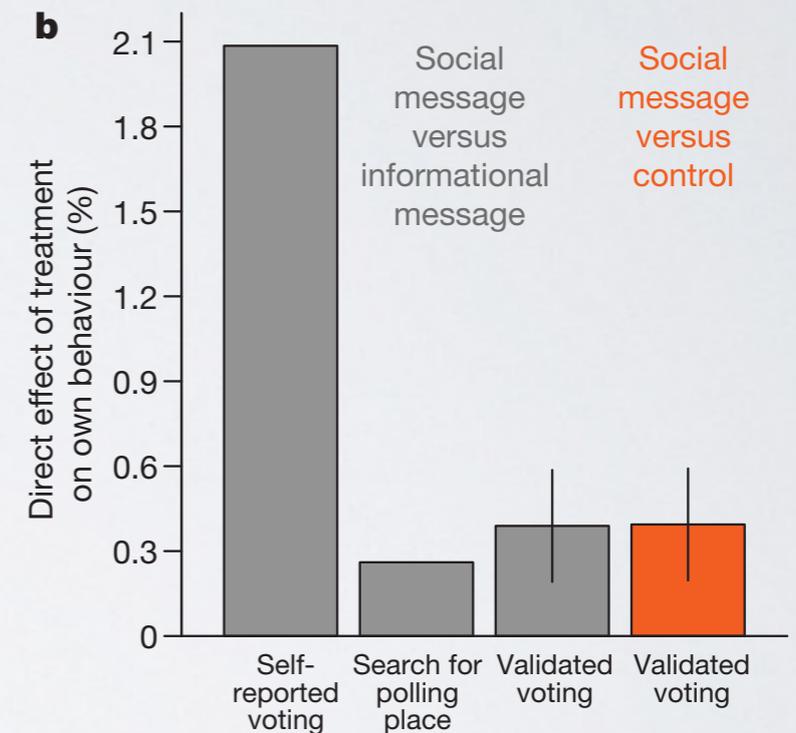
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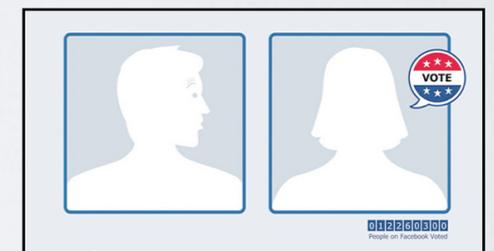
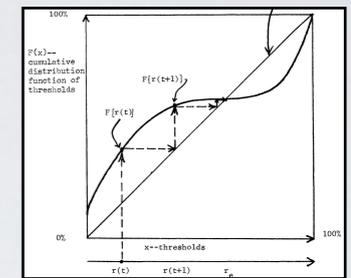
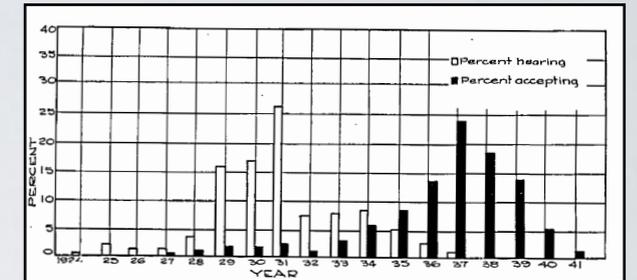


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# Timeline

- 1940s–50s: Early theories, early data
- 1960s–90s: Theory refinement/testing
- 2000s: Large-scale data
- 2010s: Large-scale experiments



**Designing/analyzing experiments to develop/test network theories**

**= Big opportunity**

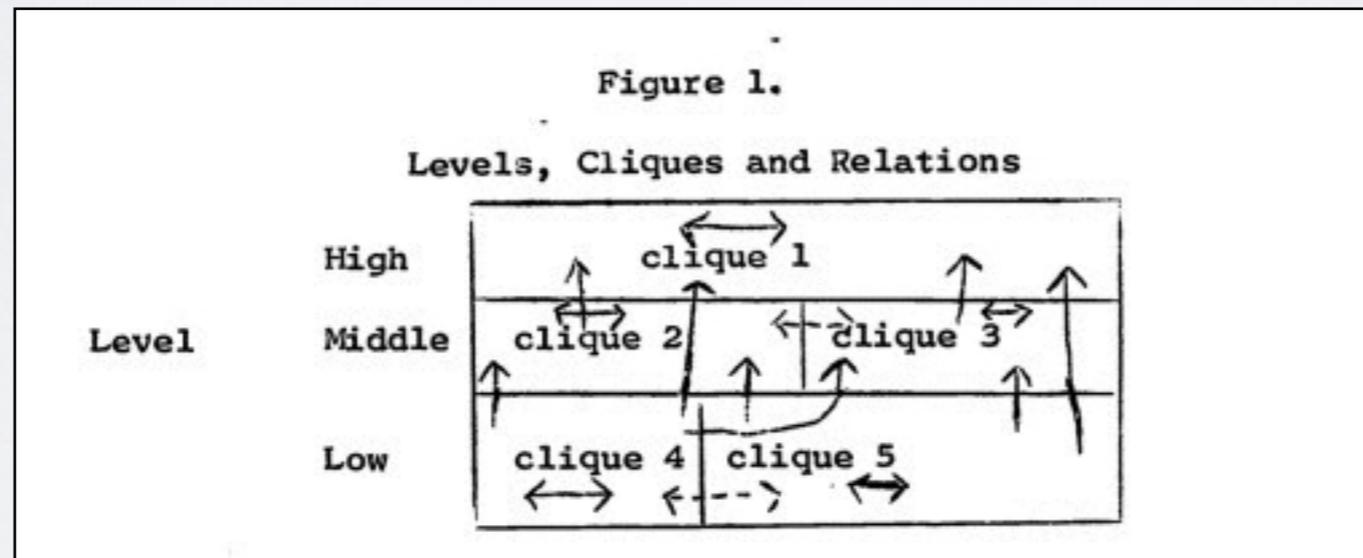
# Whirlwind tour

- What network?
- From karate to communities
- Influence, instrumented
- Homophily vs. contagion
- Influence experiments
- Network experiments

Hopefully this lecture will convince you there are really interesting research questions you can work on.

# Testing a theory with data

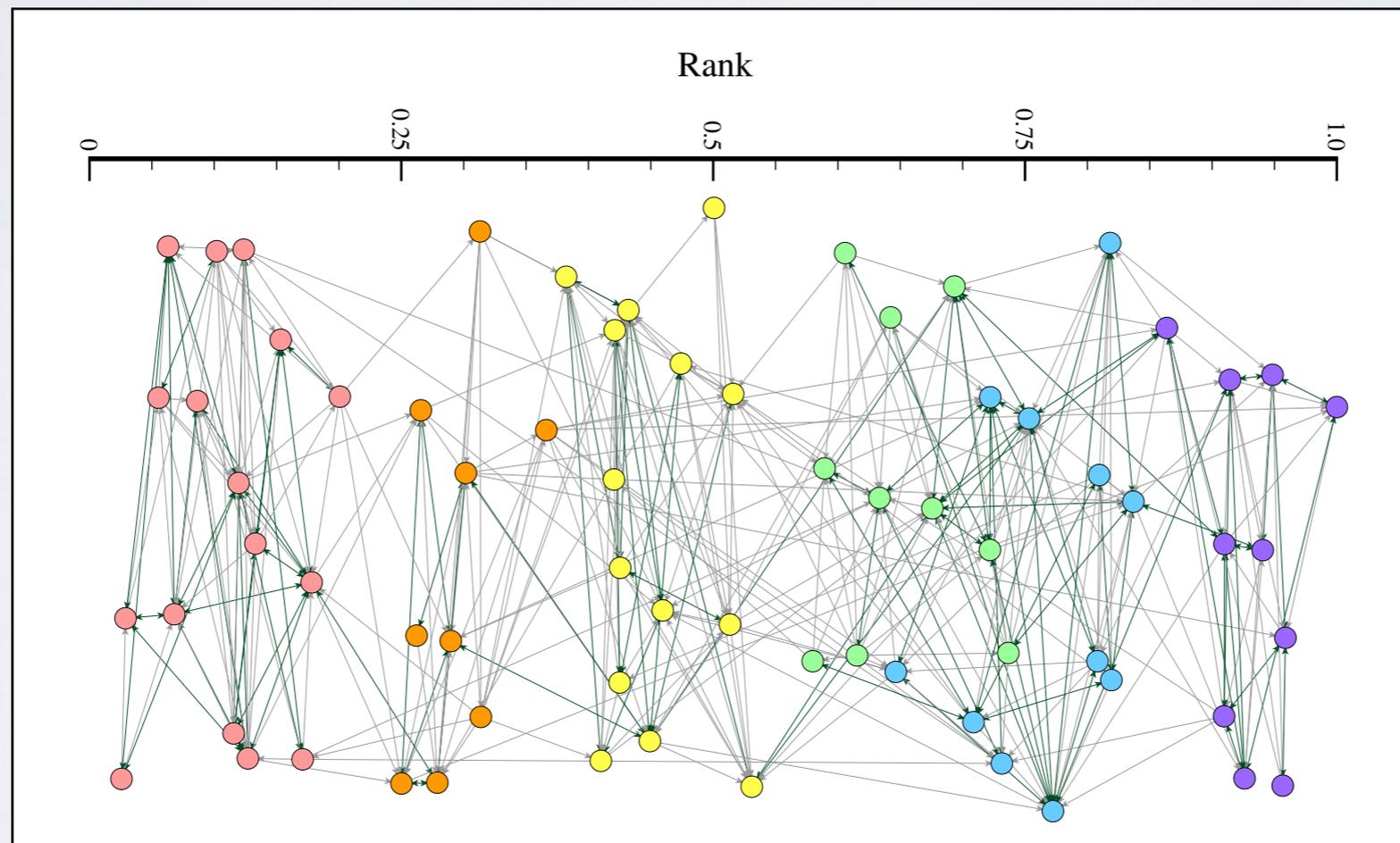
- Homans (1950): Small groups of people create a social structure that contains many clique subgroups and a ranking system.
- Davis & Leinhardt (1967): Operational statement using subgraph frequencies: some patterns less frequent than random model predicts.



- G Homans (1950) "The Human Group."
- J Davis, S Leinhardt (1971) "The structure of positive interpersonal relations in small groups," Sociological Theories in Progress.

# Extending a theory with more data

- Ball–Newman (2013): Maximum likelihood inference of status according to Homans' theory.
- Examined 84 high school networks for correlates of Homans status.



- G Homans (1950) "The Human Group."
- J Davis, S Leinhardt (1971) "The structure of positive interpersonal relations in small groups," *Sociological Theories in Progress*.
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# What network?

“Name generators” in sociology show huge difference between social networks generated by questions:

**“Who do you know?”**      **“Who are your three closest friends?”**  
**“With whom do you discuss important matters?”**

- K Campbell, B Lee (1991) “Name generators in surveys of personal networks.” *Social Networks*.
- M Resnick et al. (1997) “Protecting adolescents from harm: findings from the national longitudinal study on adolescent health.” *JAMA*.
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Ball–Newman used AddHealth, which has issues that requires care.

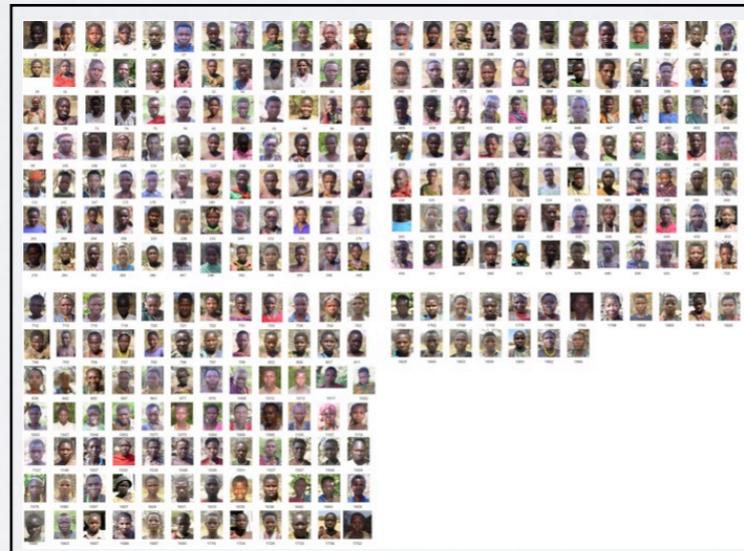
**“Up to 10 people with whom they are friends,  
with a maximum of five being male and 5 being female”**

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“With whom they would like to live in the next camp”

“To whom they would give an actual gift of honey”

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# Online Social Networks



Acquaintances, often international. Business and personal.



2004: classmates, 2015: most people you know who are online.



Mostly professional connections, some friends.



Virtual acquaintances, often interest-driven.



Photography-interested real-world/virtual friends.



People you talk to on the phone, including customer service.



Close friends who exercise.



Sometimes personal, sometimes professional, sometimes both.

# Online Social Networks



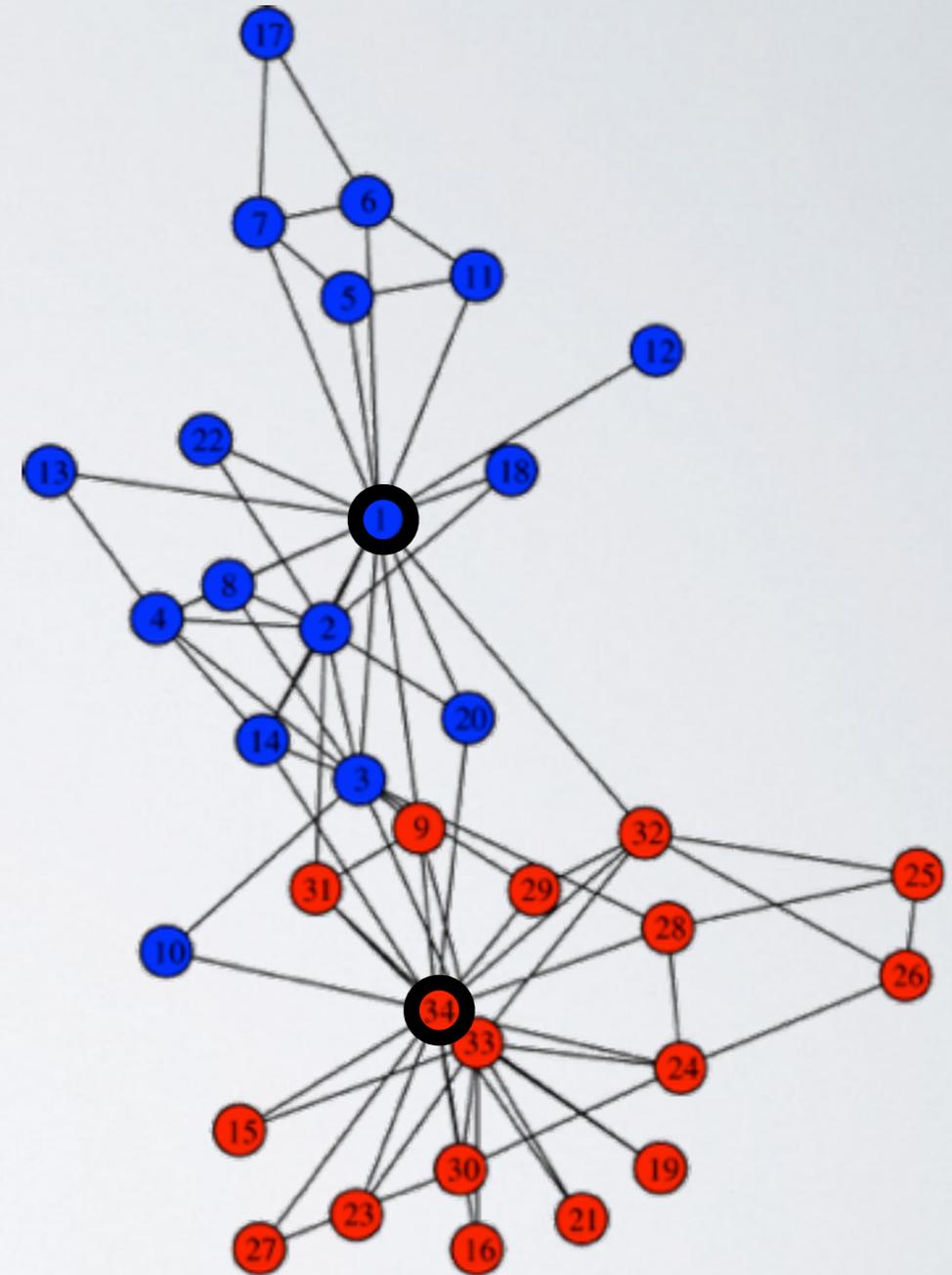
Some differences:

- Design aspects
- Personal vs. professional
- Strong vs. weak (Onnela et al. 2007)
- Virtual/real-world acquaintances (Jacobs et al. 2015)
- Single interest vs. diverse interest networks
- Co-tag friends vs. news feed friends vs. chat friends
- Phone calls vs. texts
- ...

- JP Onnela et al. (2007) "Structure and tie strengths in mobile communication networks," PNAS.
- AZ Jacobs, SF Way, J Ugander, A Clauset (2015) "Assembling thefacebook: Using Heterogeneity to Understand Online Social Network Assembly," WebSci.

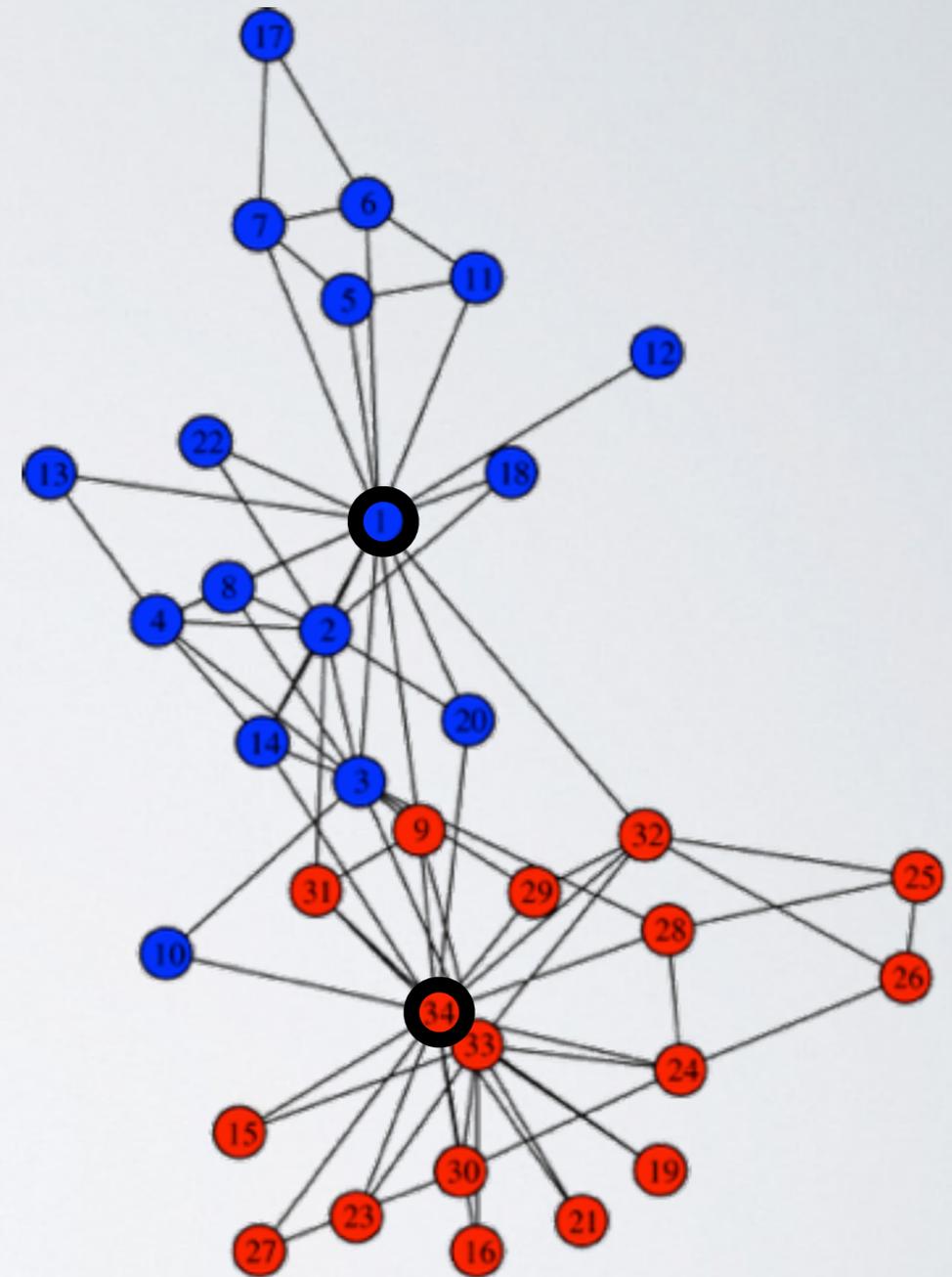
# Zachary Karate Club

- Wayne Zachary, sociologist interested in group dynamics.
- Edges: interacted outside the club
- Studied a karate club for 3 years ('70-'72)
- Club formed factions around instructor (1) and Club President (34).
- Zachary was interested in if faction structure could be predicted.
- Method?



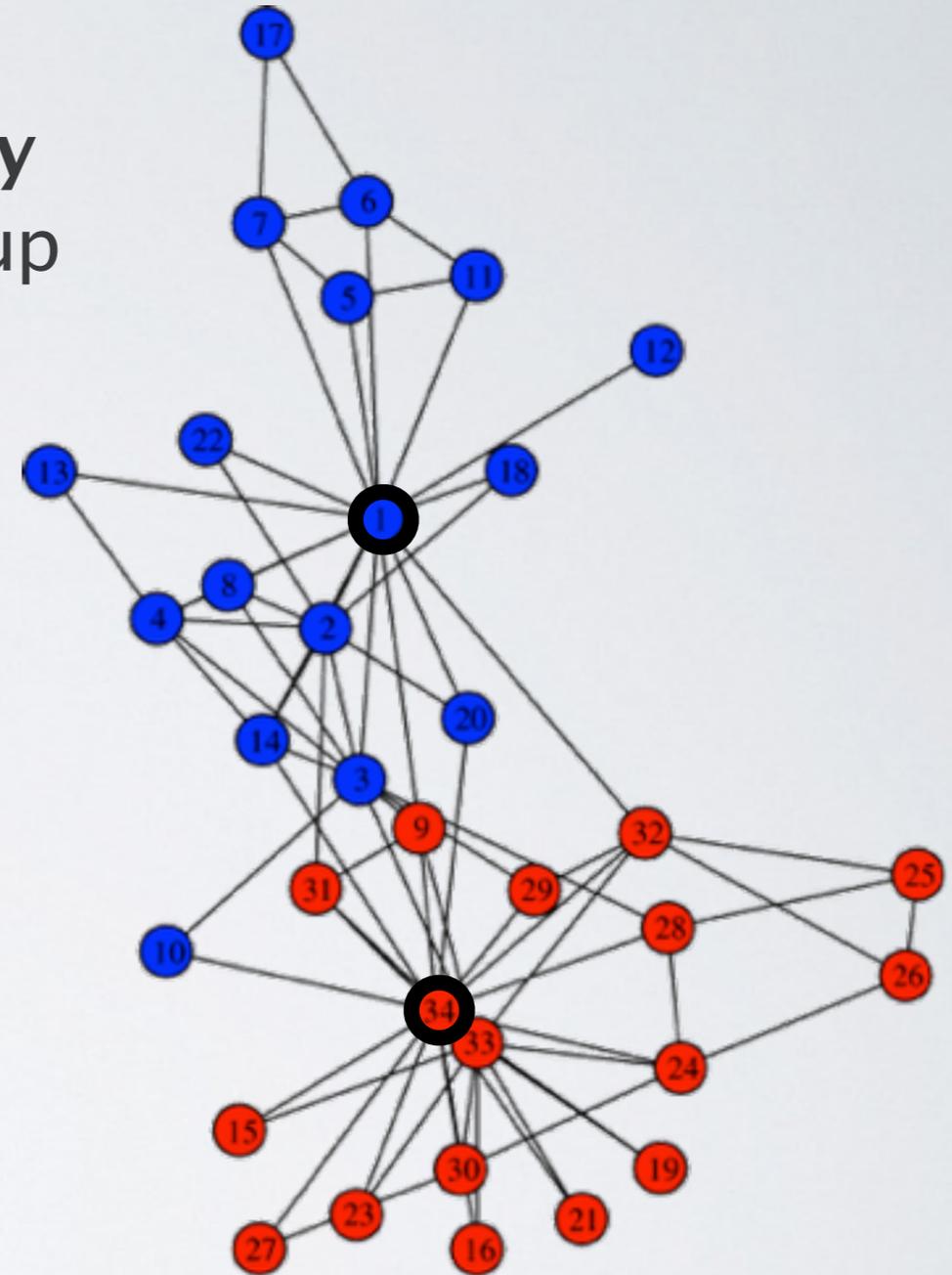
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- **Network Flow!** Applied Ford–Fulkerson, found group split was predicted by min–cut.



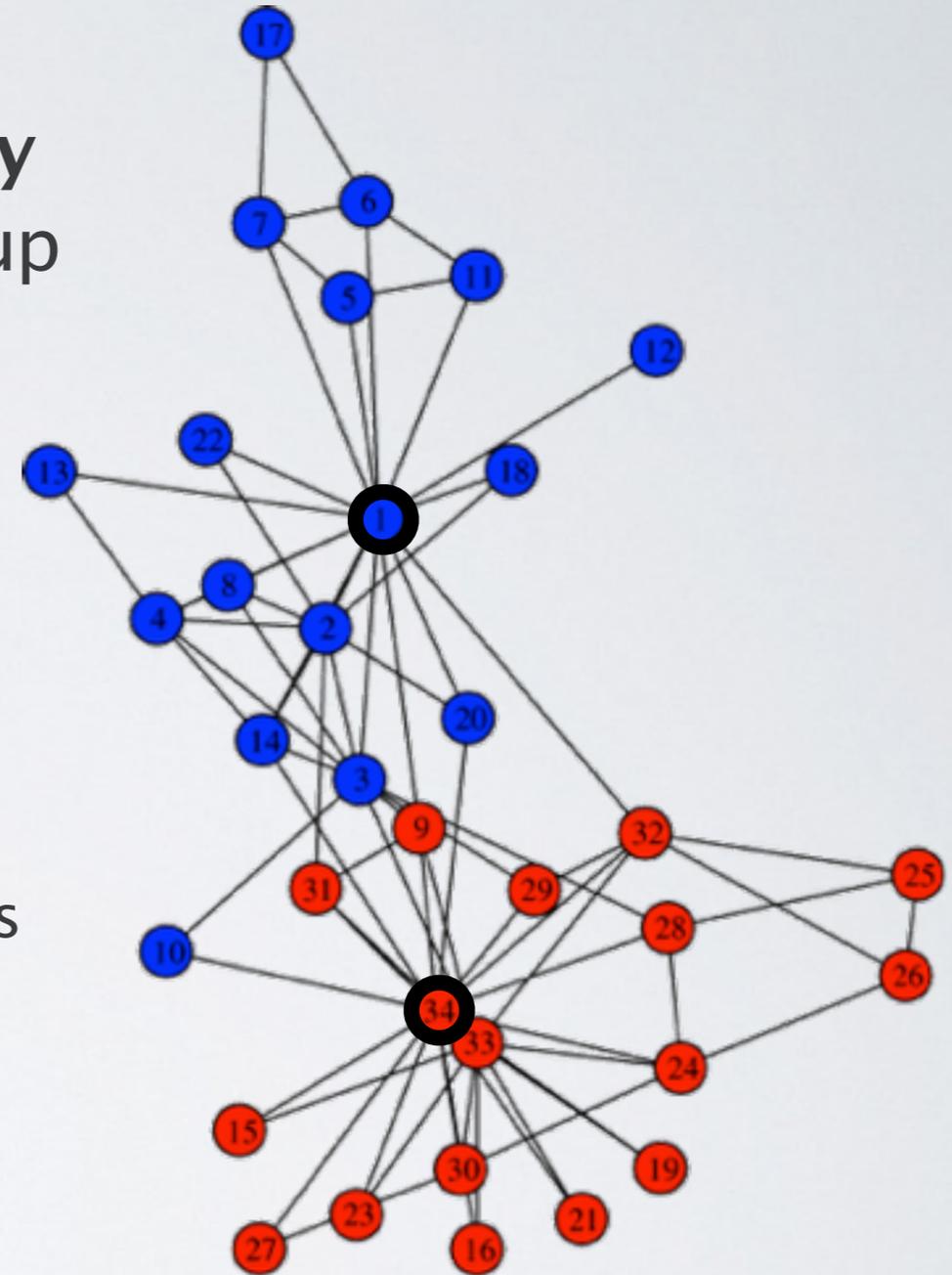
# From Karate to Communities

- Zachary “objective function” for community detection: does algorithm predict how a group fissions when led by two rival leaders?



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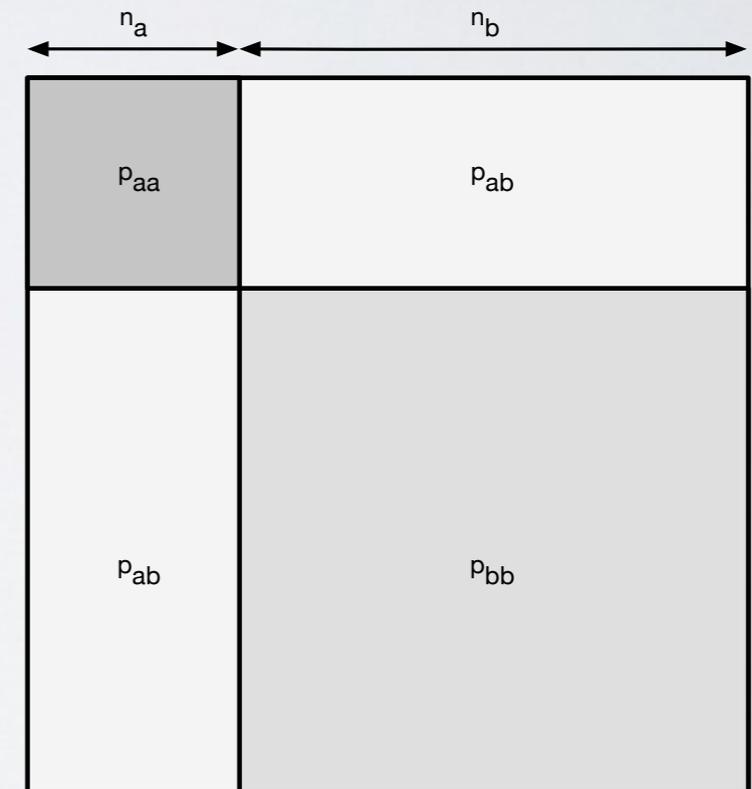
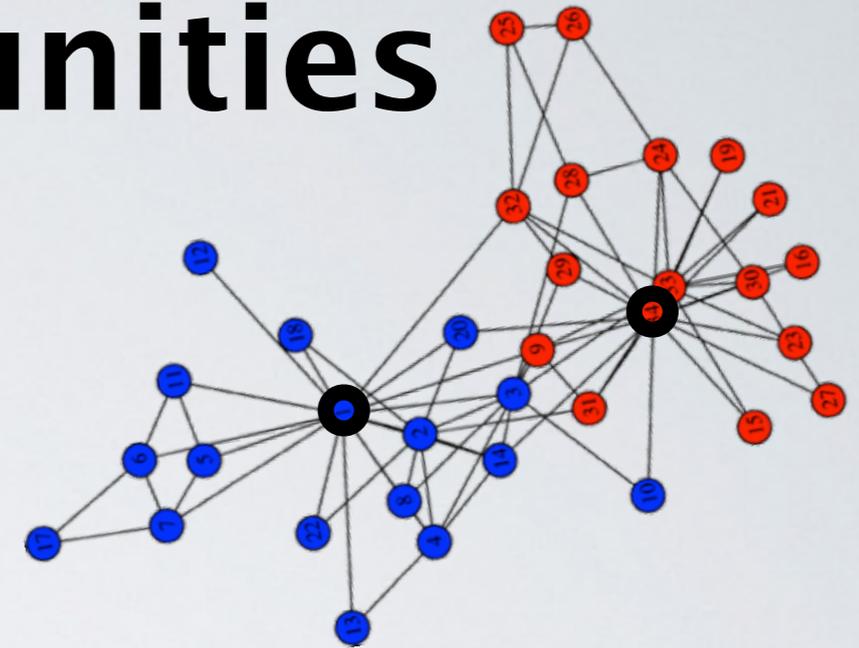
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- Other objectives
  - Modularity maximization:
    - Has “resolution limit”
  - Conductance (normalized min-cut):
    - Produces balanced partitions; spectral guarantees



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- J Shi, J Malik (2000) "Normalized cuts and image segmentation," IEEE Trans Pattern Analysis and Machine Intelligence.
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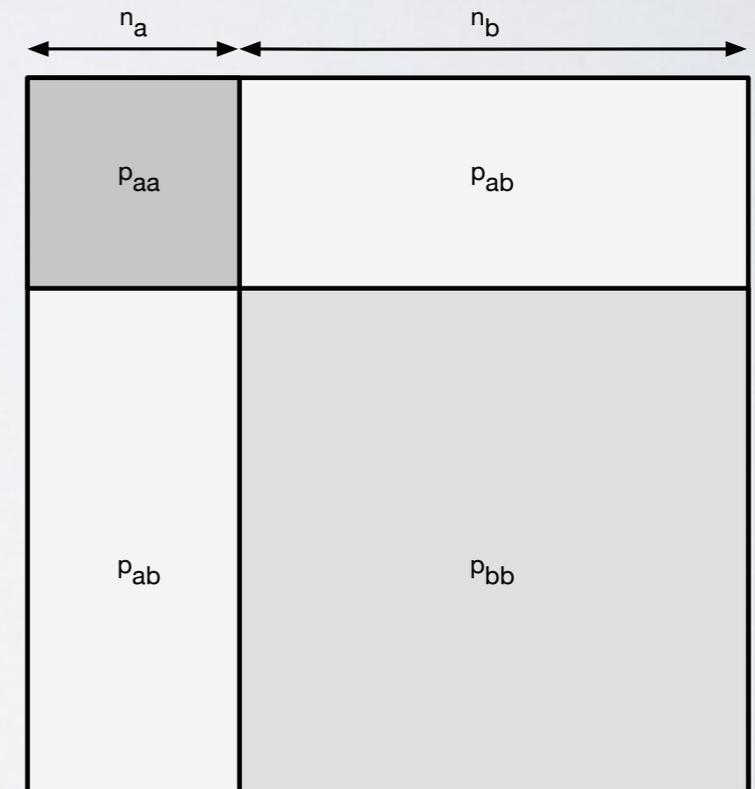
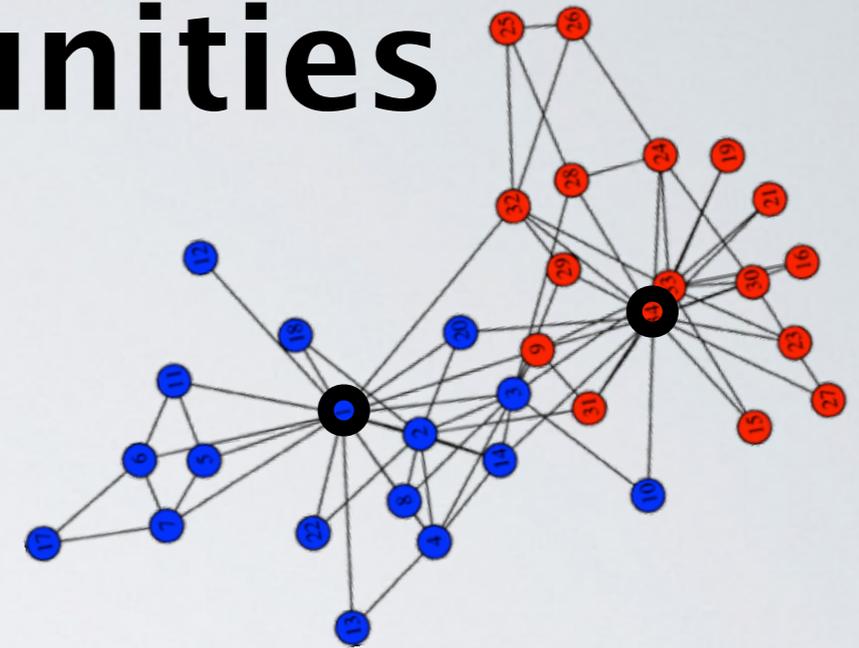
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    - Stylized model in absence of ground truth data



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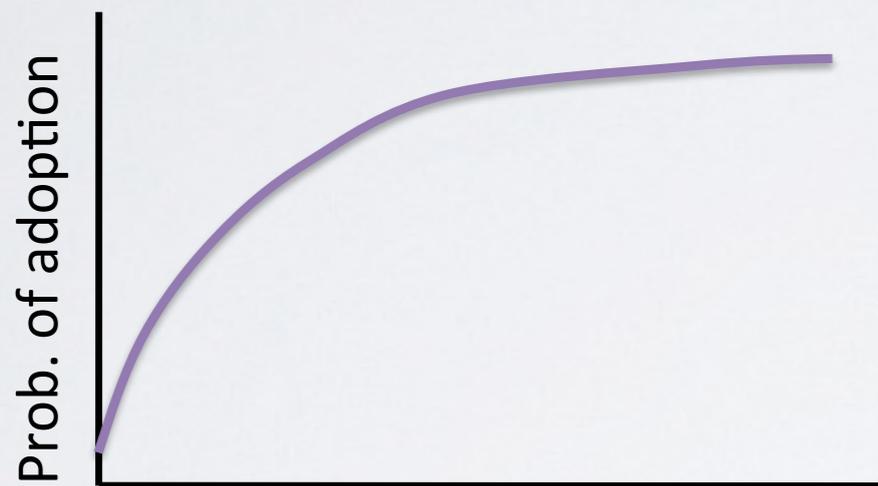
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  - Use in clustered network experiments?



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# Influence, instrumented

- Prob. of adoption depends on the number of friends who have adopted (Bass 1969, Granovetter 1978)
- What is the shape? Diminishing returns? Critical mass?



k = number of friends adopting

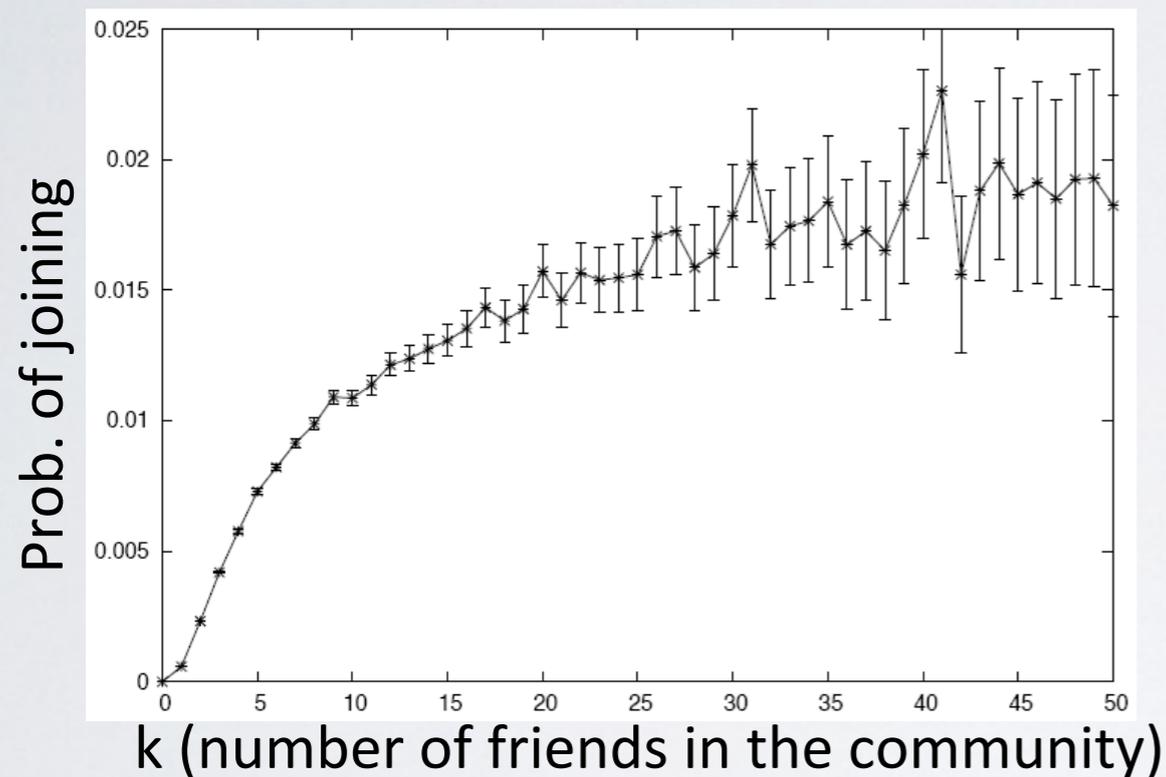


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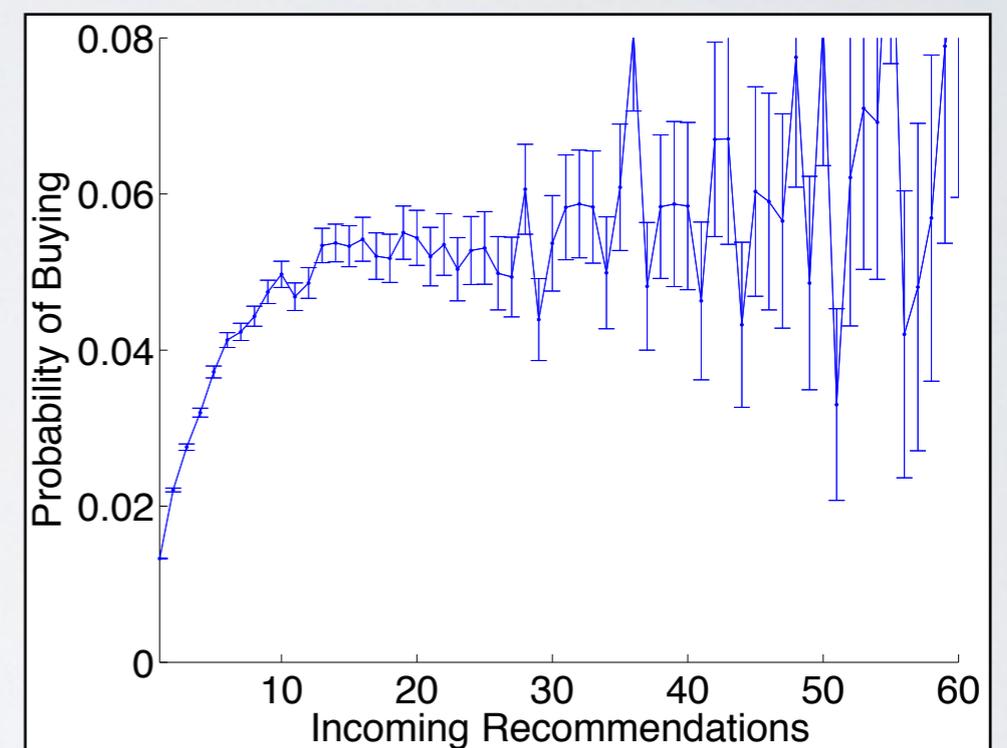
- F Bass (1969) "A new product growth for model consumer durables". Management Science.
- M Granovetter (1978) "Threshold models of collective action," American Journal Sociology.
- D Watts, P Dodds (2007) "Influentials, Networks, and Public Opinion Formation" Journal of Consumer Research.

# Influence, instrumented

Backstrom et al. 2006: Probability of joining LiveJournal group



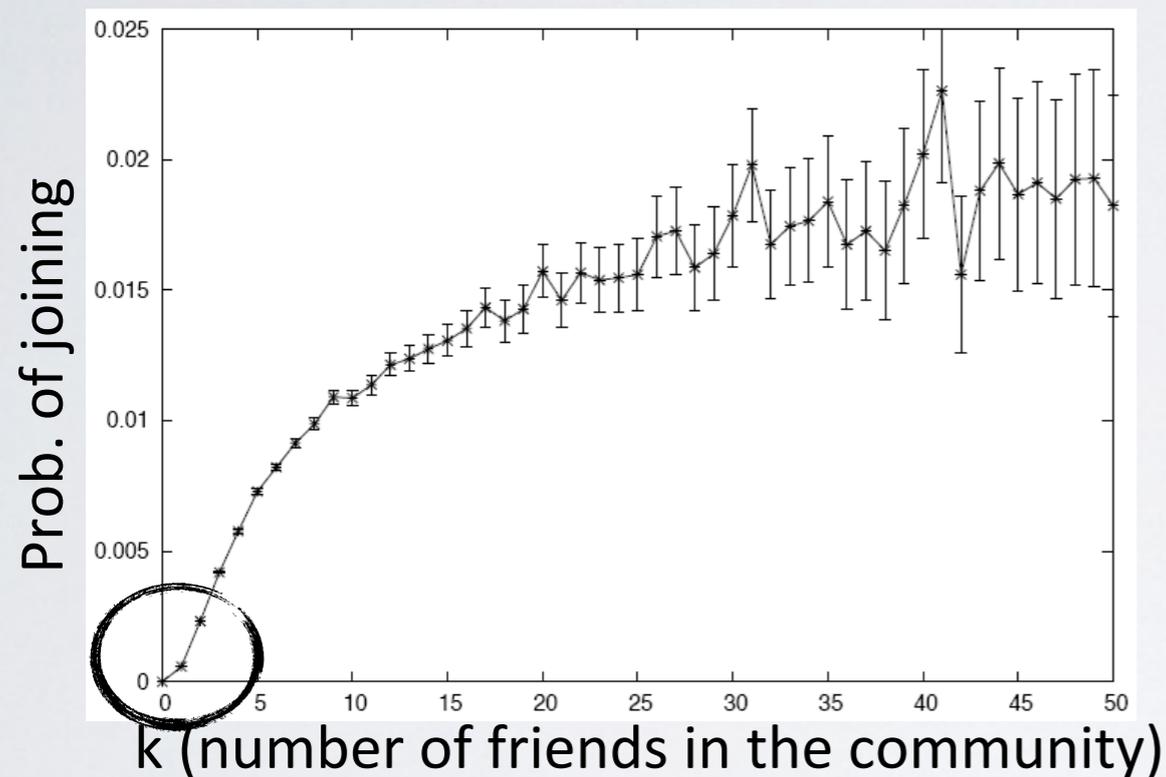
Leskovec et al. 2006: Probability of buying a DVD



- L Backstrom, D Huttenlocher, J Kleinberg, X Lan (2006) "Group formation in large social networks: membership, growth, and evolution," KDD.
- J Leskovec, LA Adamic, BA Huberman (2006) "The dynamics of viral marketing," EC.
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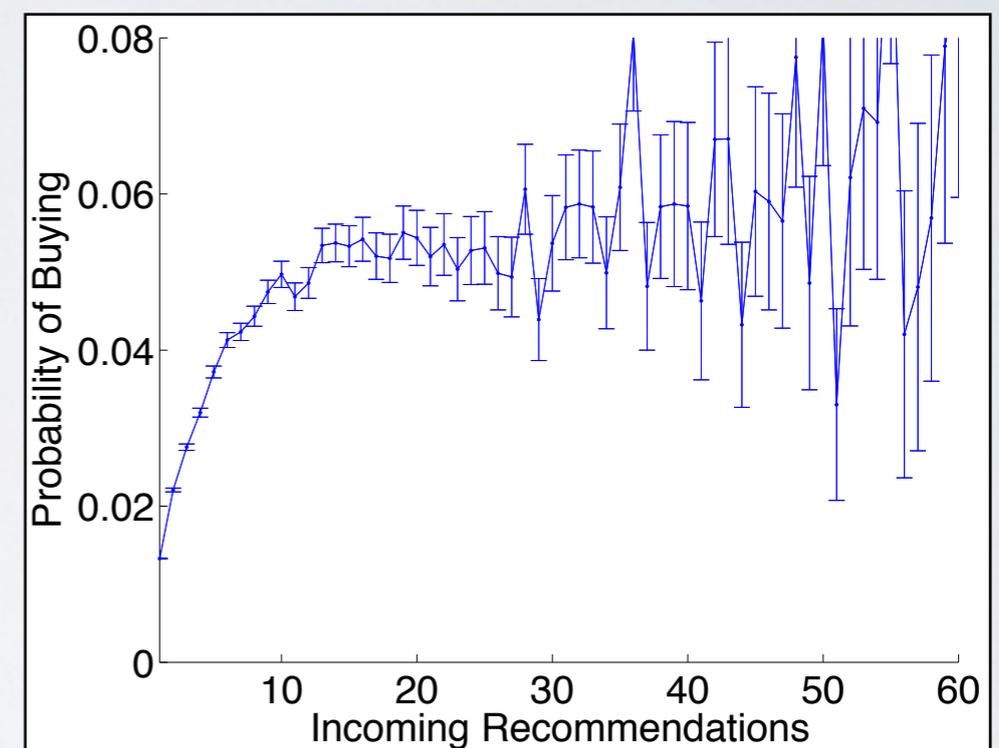
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Complex contagion?

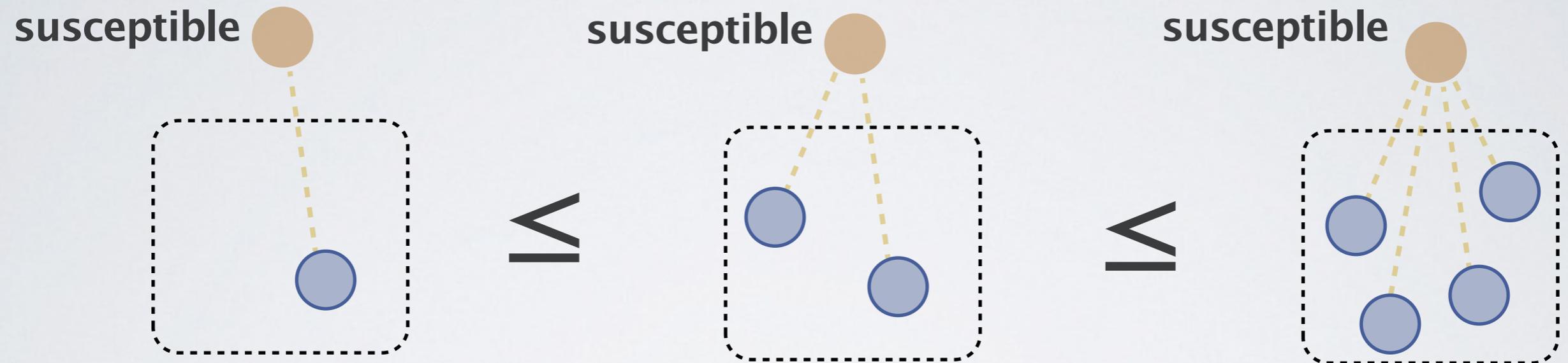
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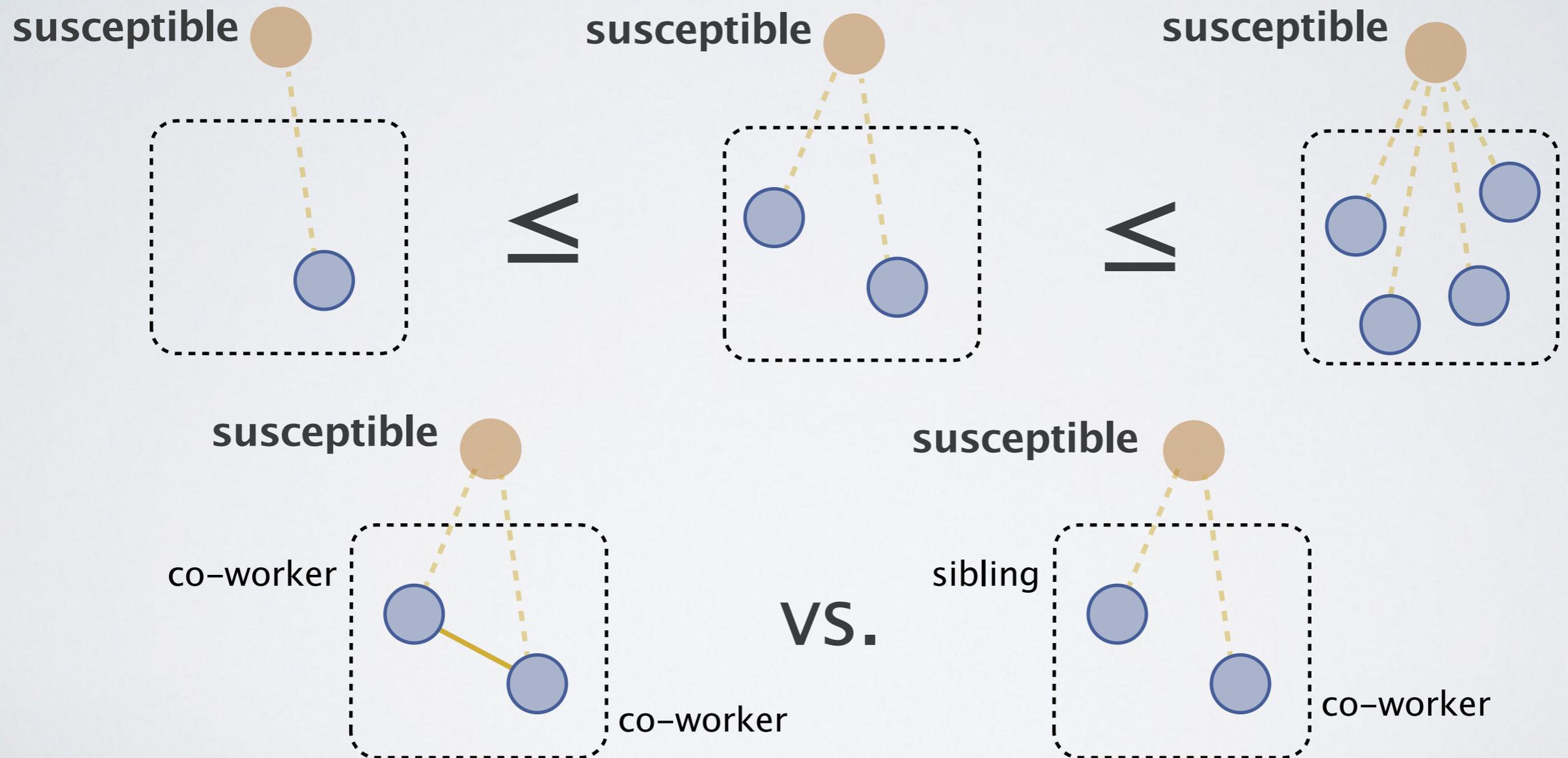
# Influence and graph structure

- Adoption as a simple function of ‘contact neighborhood’ size:



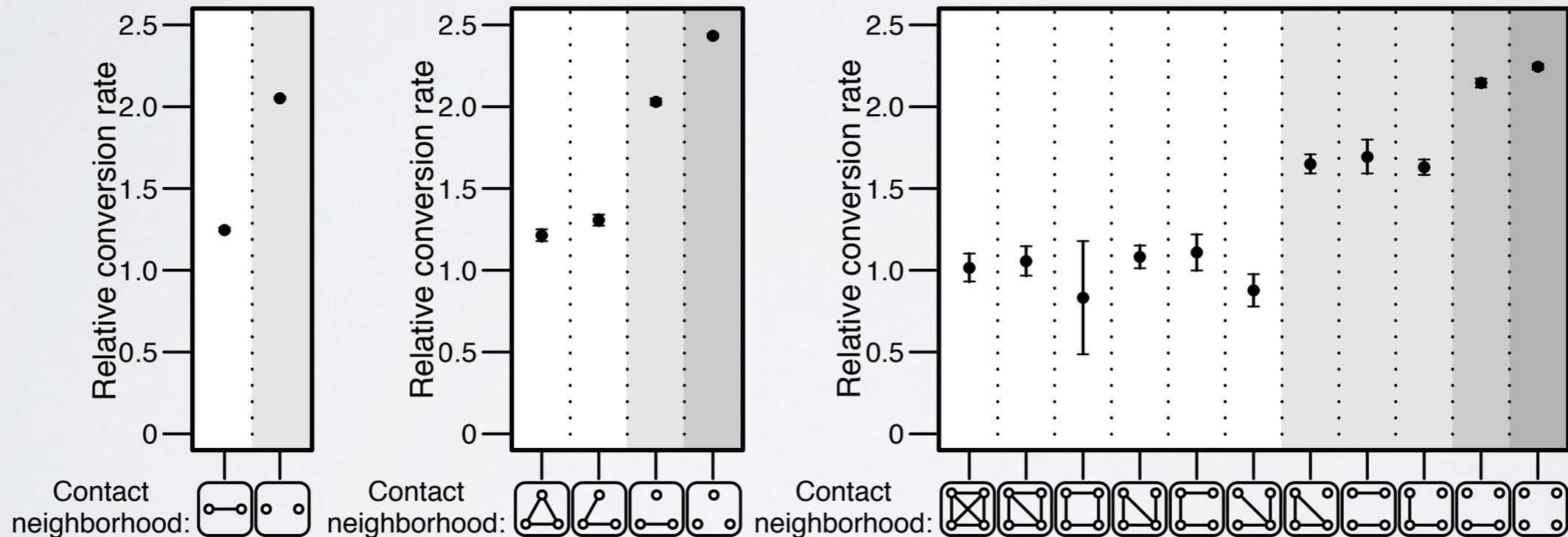
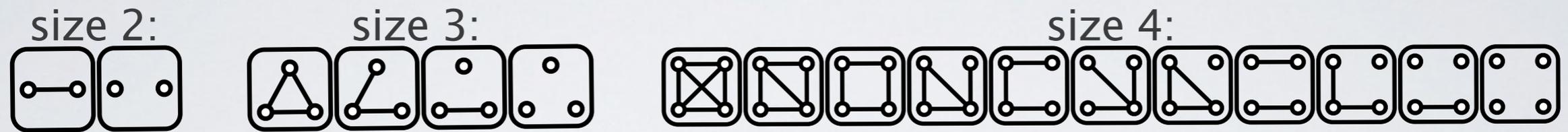
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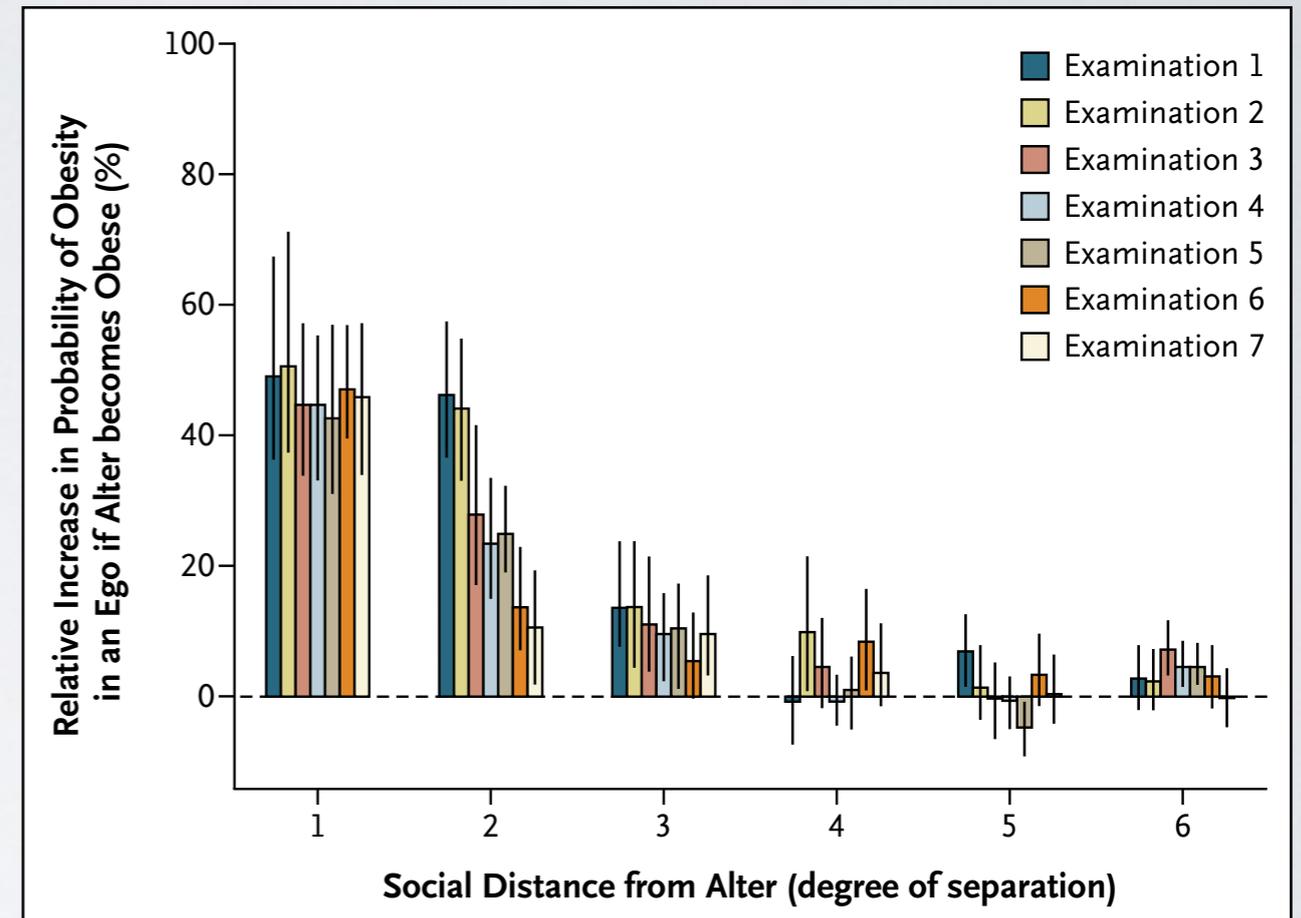
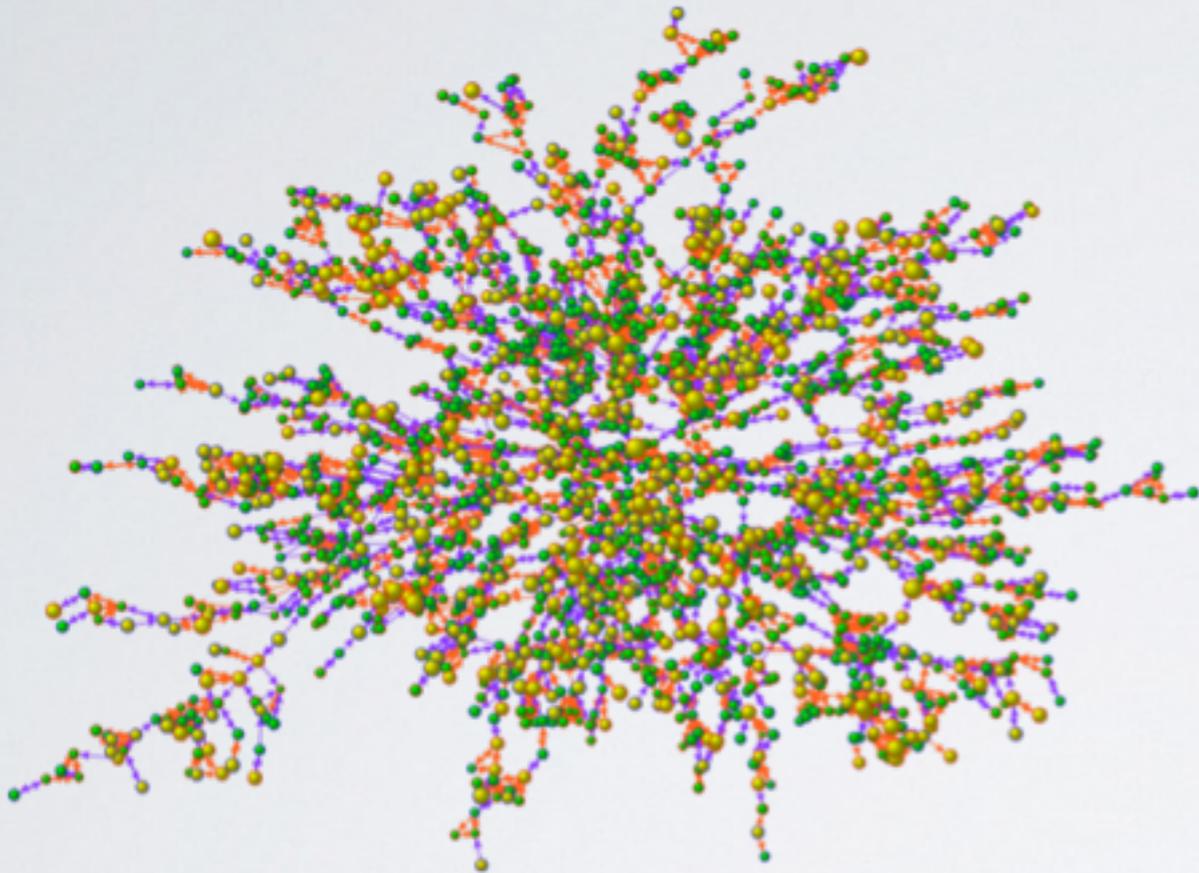
# Structural diversity

Conversion rate on invitations to Facebook as a function of graph, “f(G)”?



- J Ugander, L Backstrom, C Marlow, J Kleinberg (2012) “Structural diversity in social contagion,” PNAS.

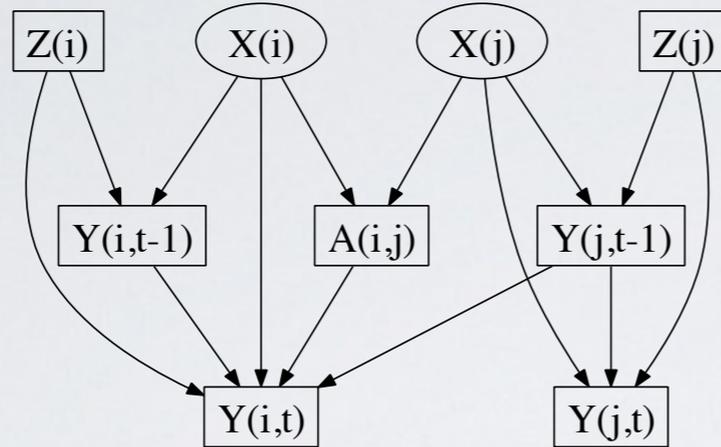
# Is obesity contagious?



“comparing the conditional probability of obesity in the observed network with the probability of obesity in identical networks (with topology preserved) in which the same number of obese persons is randomly distributed”

- N Christakis, J Fowler (2007) "The Spread of Obesity in a Large Social Network over 32 Years," New England J of Medicine.
- C Shalizi, A Thomas (2011) "Homophily and contagion are generically confounded in observational social network studies," Sociological Methods & Research.

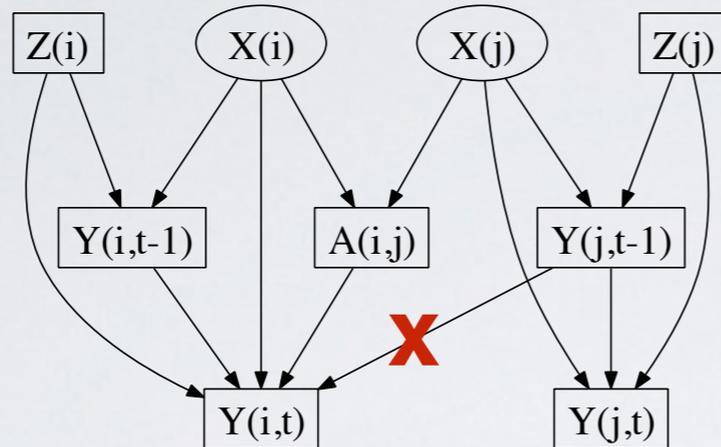
# Knock-out experiments



Symbol	Meaning
$i, j$	Individuals
$Z$	Observed Traits
$X$	Latent Traits
$Y$	Observed Outcomes

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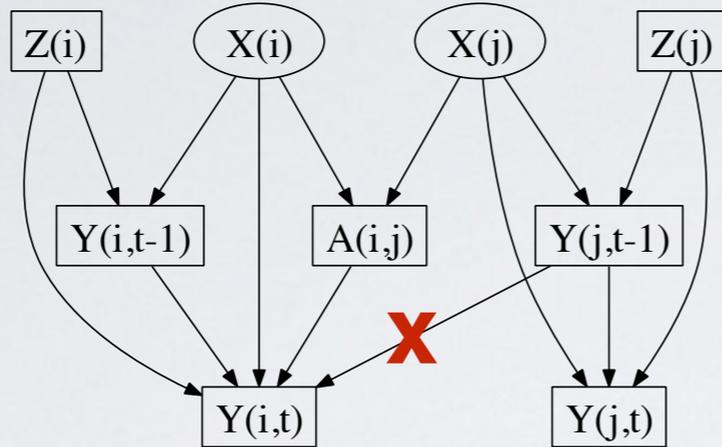
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“Feed Condition”

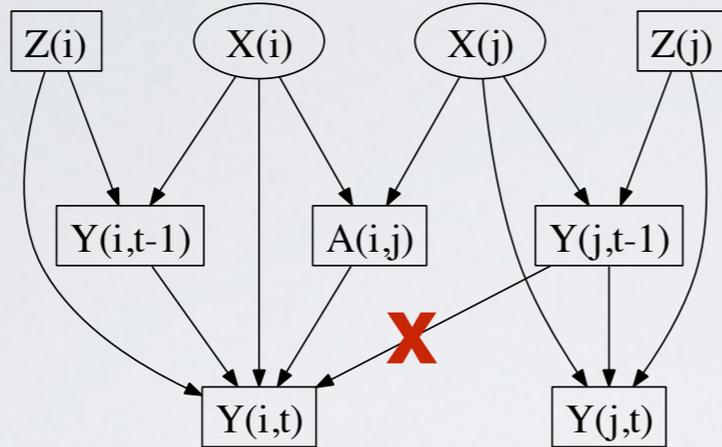


“No Feed Condition”



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“Feed Condition”



“No Feed Condition”

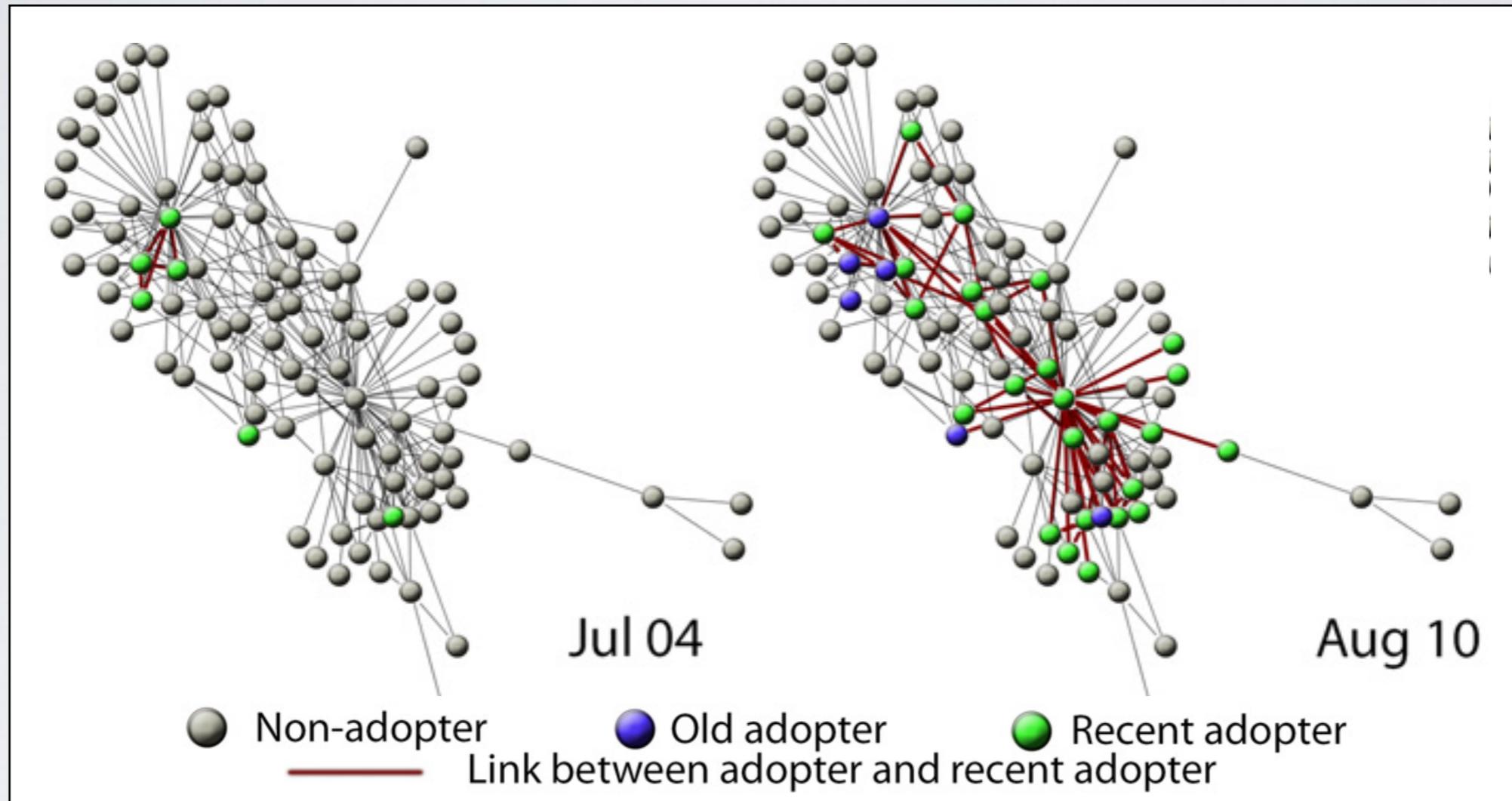


Feed condition:  
**7.37x**  
 more likely to share.

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# Do we need experiments?

- (Aral et al. 2009): Yahoo! Go service, 2007, n=27.4 million.

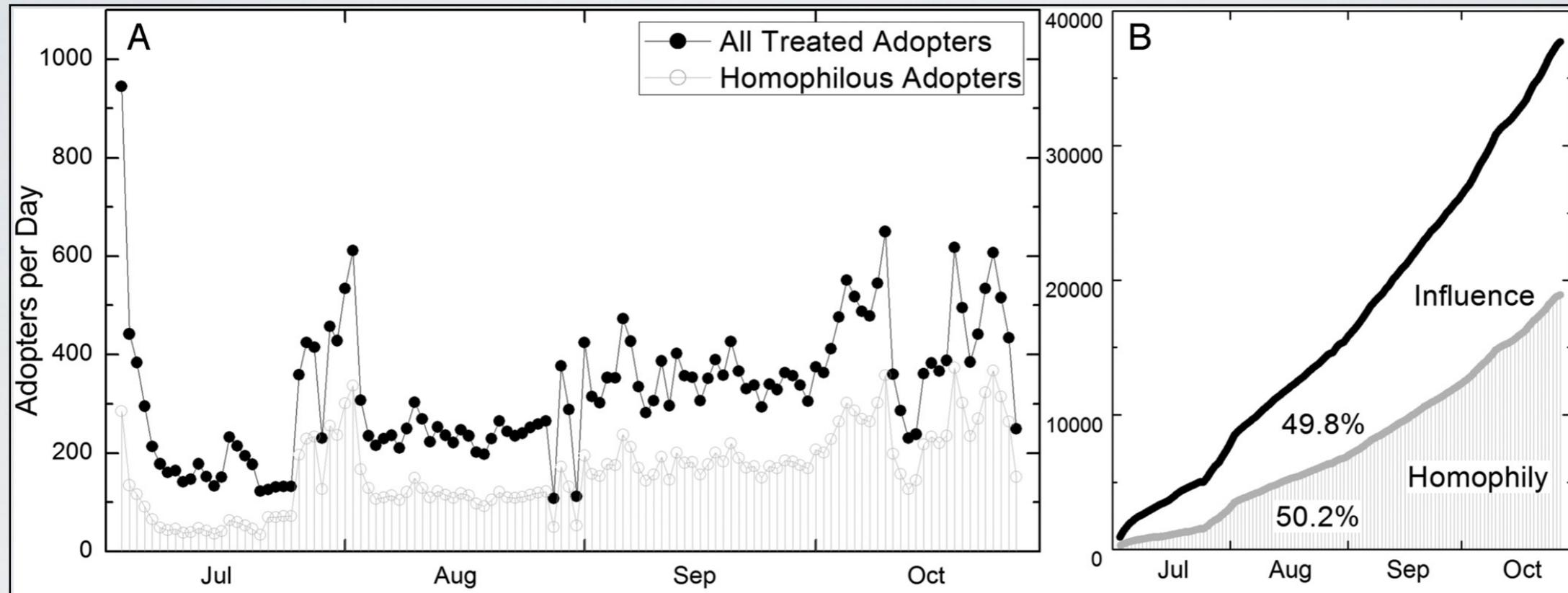


Is this social influence?

- P Rosenbaum, D Rubin (1983) "The central role of the propensity score in observational studies for causal effects," Biometrika.
- D Rubin (2006) "Matched sampling for causal effects"
- S Aral, L Muchnik, A Sundararajan (2009) "Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks," PNAS.

# Do we need experiments?

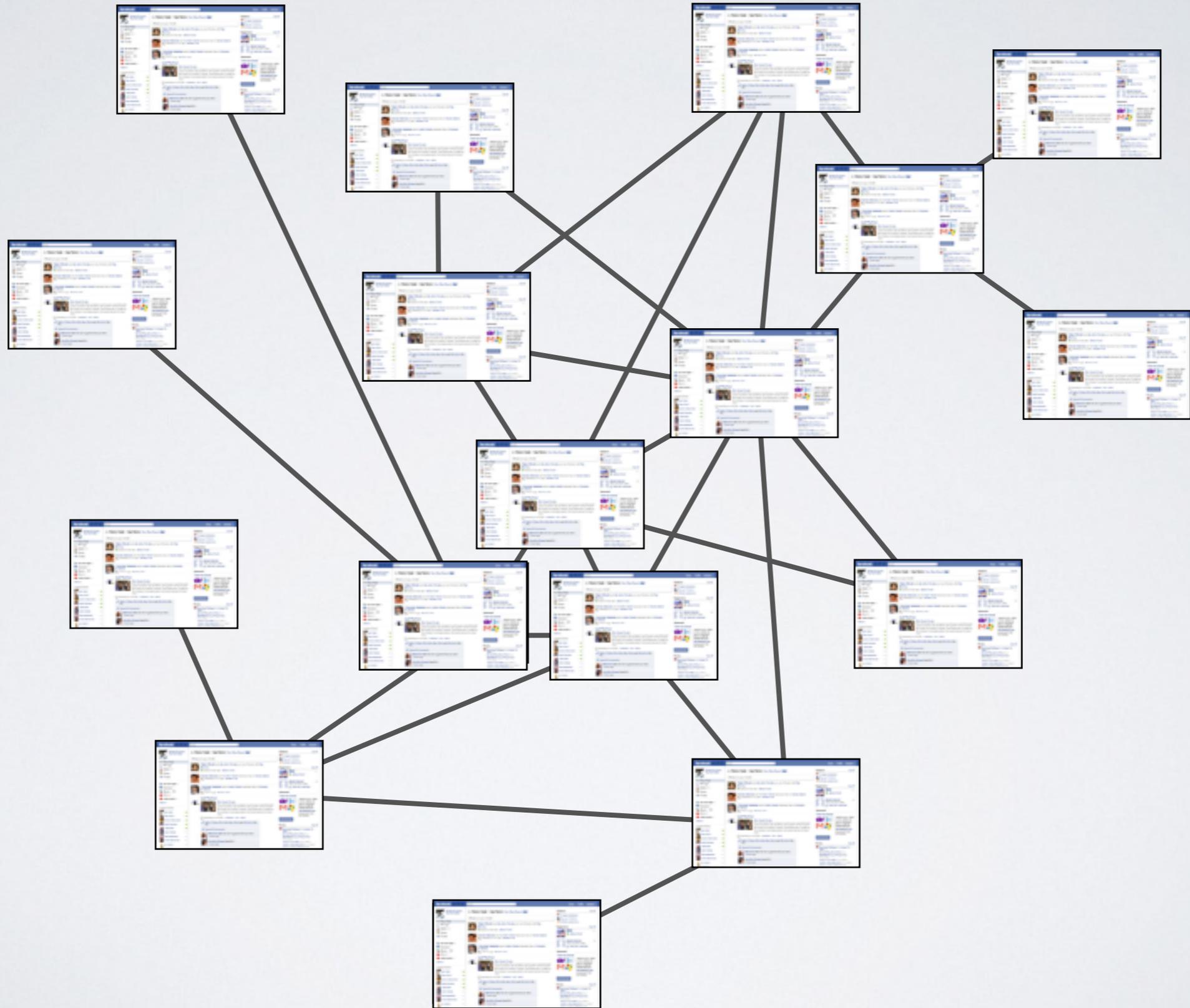
- (Aral et al. 2009): Yahoo! Go service, 2007, n=27.4 million.



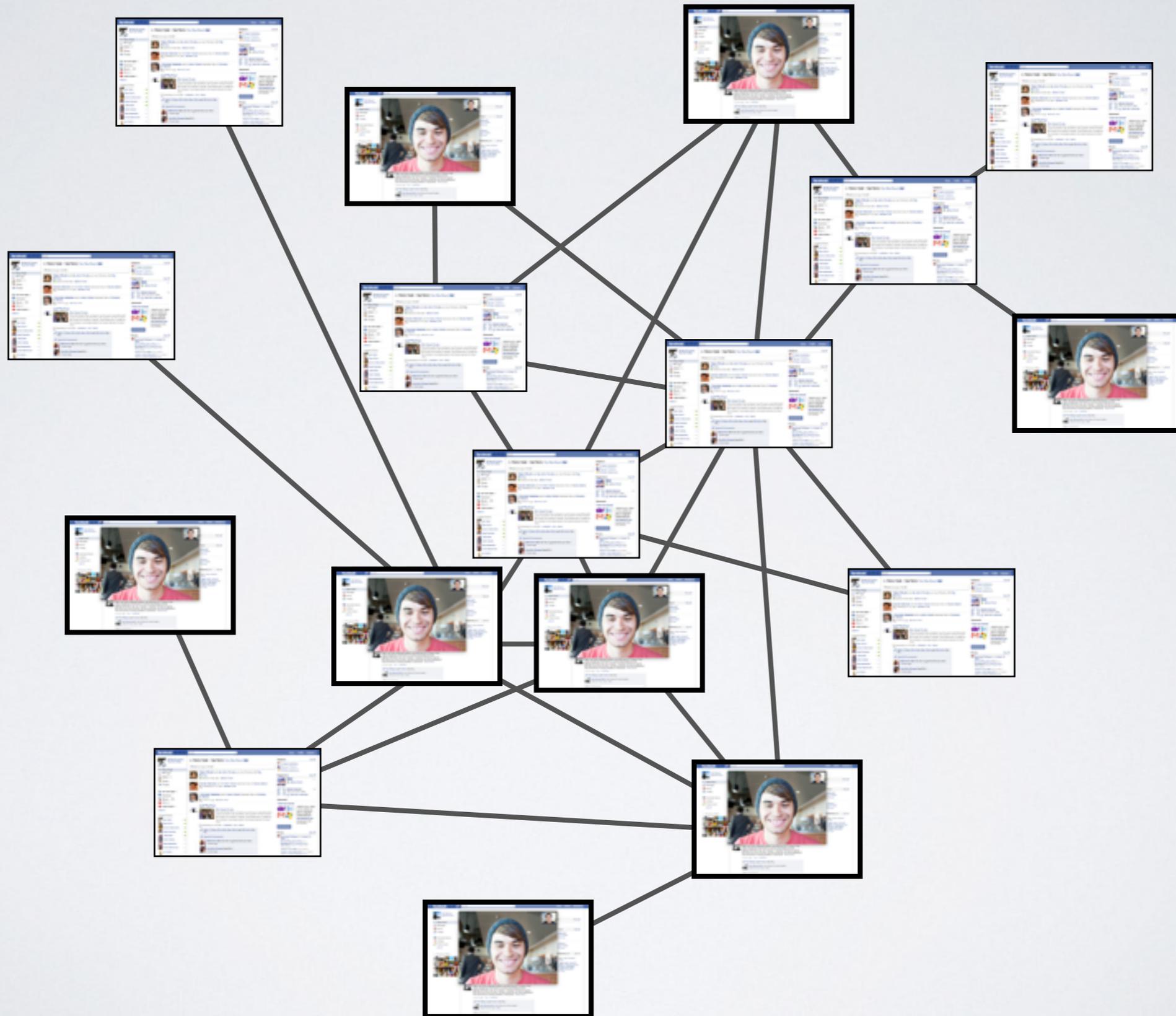
Is this social influence? ~50%

- P Rosenbaum, D Rubin (1983) "The central role of the propensity score in observational studies for causal effects," Biometrika.
- D Rubin (2006) "Matched sampling for causal effects"
- S Aral, L Muchnik, A Sundararajan (2009) "Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks," PNAS.

# A/B testing under network effects

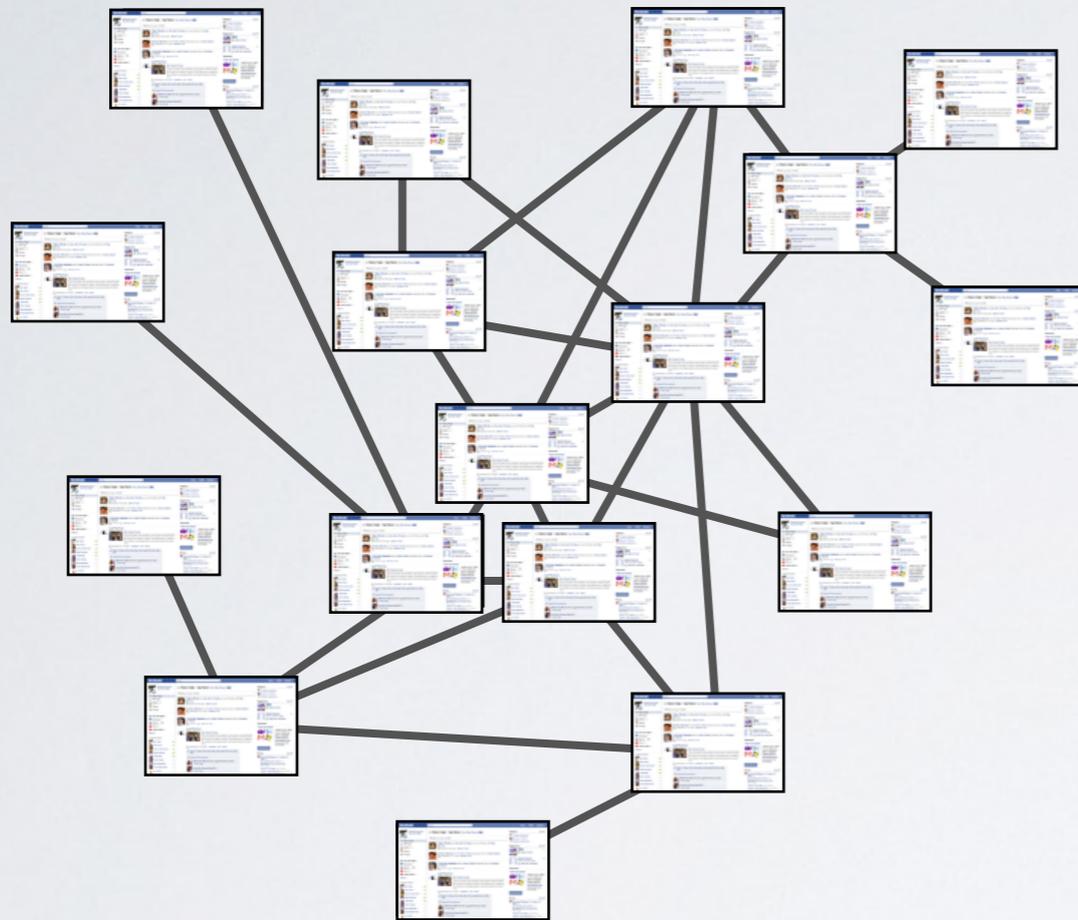


# A/B testing under network effects

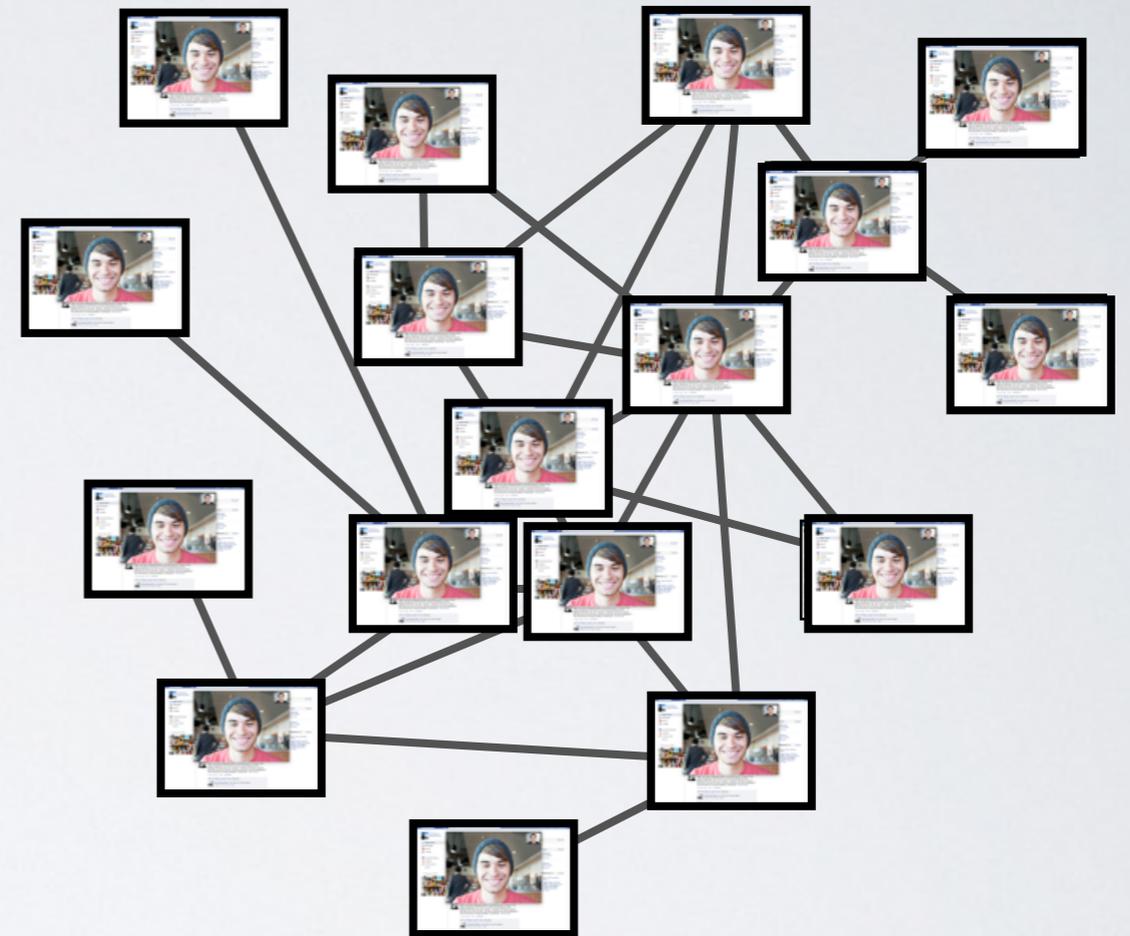


# Causal inference & network effects

Universe A



Universe B

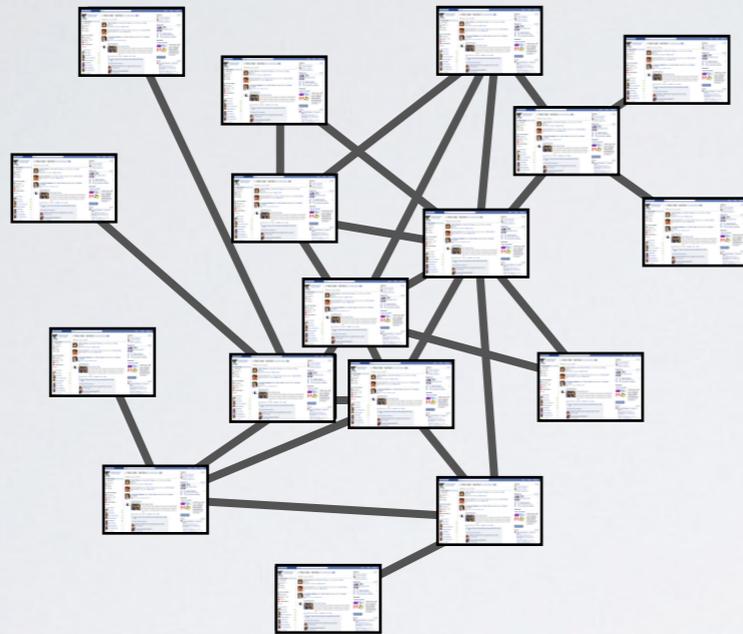


**Fundamental problem:** want to compare (average treatment effect, ATE), but can't observe network in both states at once.

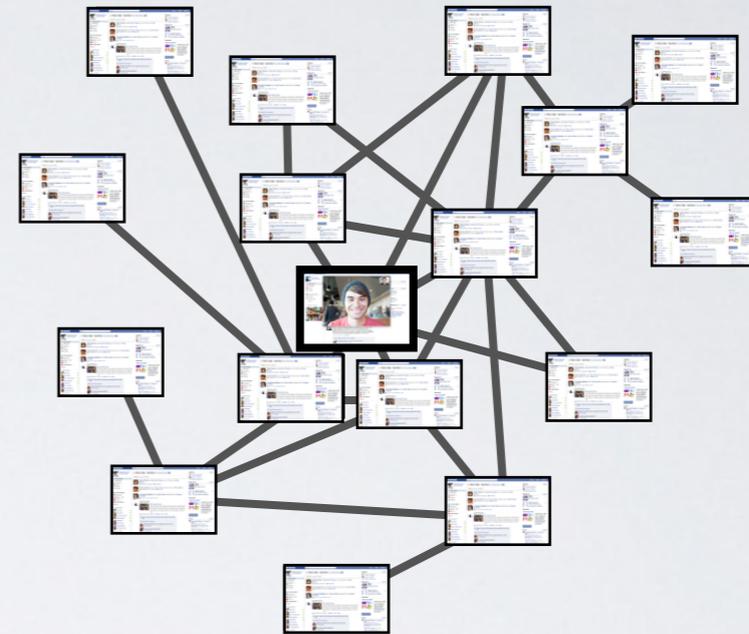
- J Ugander, B Karrer, L Backstrom, J Kleinberg (2013) "Graph Cluster Randomization: Network Exposure to Multiple Universes," KDD.
- D Eckles, B Karrer, J Ugander (2014) "Design and analysis of experiments in networks: Reducing bias from interference," arXiv.
- S Athey, D Eckles, G Imbens (2015) "Exact P-values for Network Interference," arXiv.

# Direct vs. indirect effects

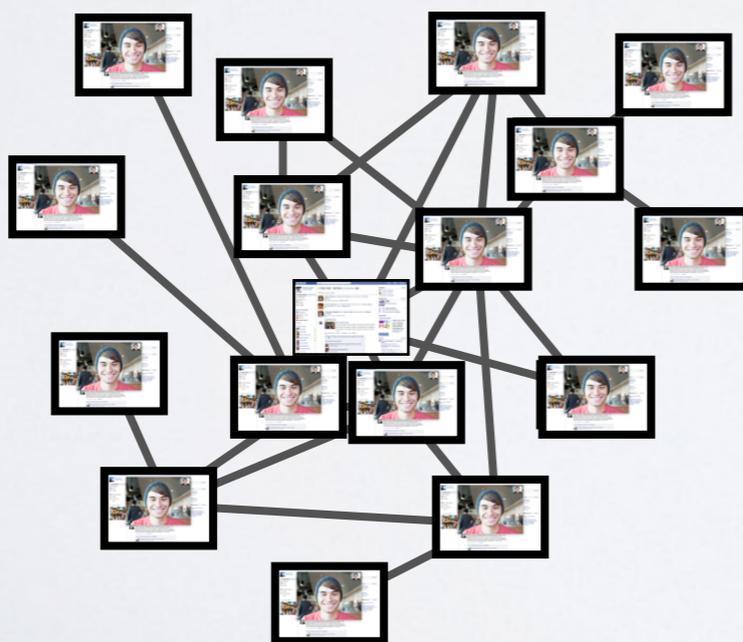
Universe A



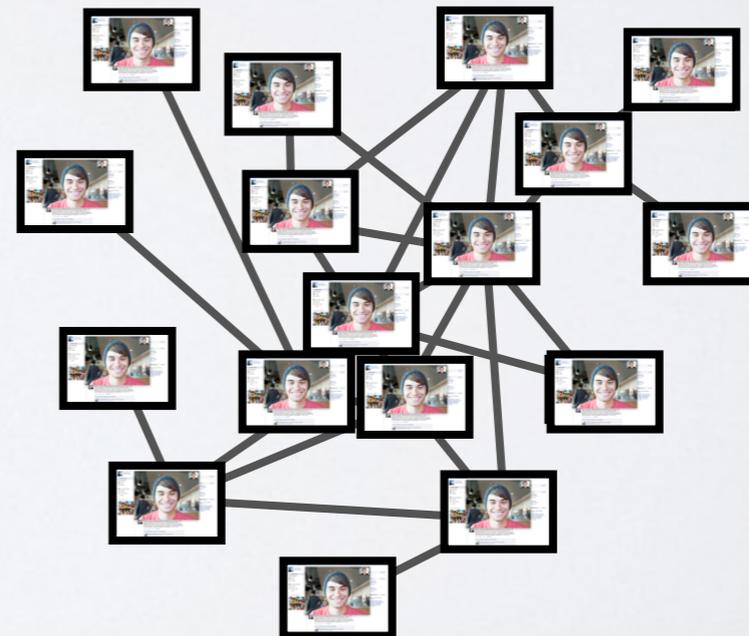
Direct effect



Indirect effect



Universe B



- P Aronow, C Samii (2013) "Estimating average causal effects under interference between units," arXiv.
- C Manski (2013) "Identification of treatment response with social interactions," The Econometrics Journal.

# Learning outcomes

1. Students should develop a familiarity with relevant structural properties of empirical social networks, and how different graph models capture or don't capture these properties.
2. Students should be able to weigh advantages and disadvantages of different observational and experimental study designs that examine/test mechanisms in social systems.
3. Students should be able to employ structural measures for diverse ranking/predicting problems on graphs.
4. Students should be able to critically read research papers in the field to identify strengths and potential weaknesses, and to be able to design tests of potential weaknesses.