Tutorial:
Social Network Models and Data

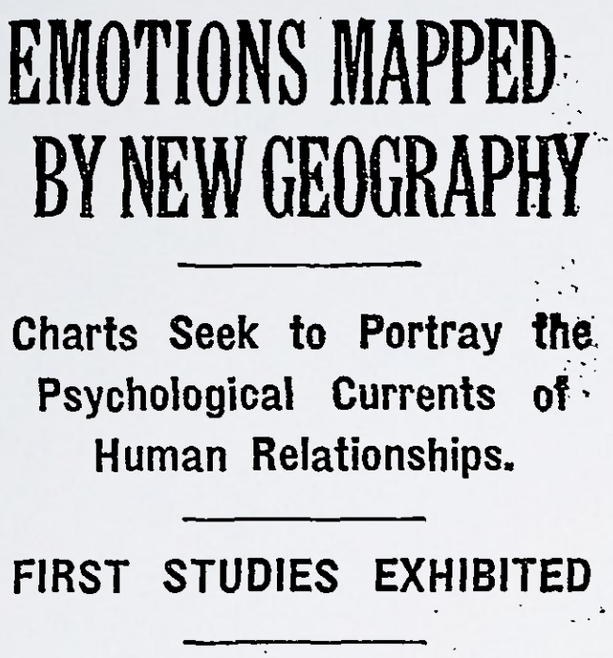
http://www.stanford.edu/~jugander/ec-tutorial/

Johan Ugander, Microsoft Research
(with Jure Leskovec, Stanford)

ACM EC Tutorial
June 16, 2015

Microsoft Research

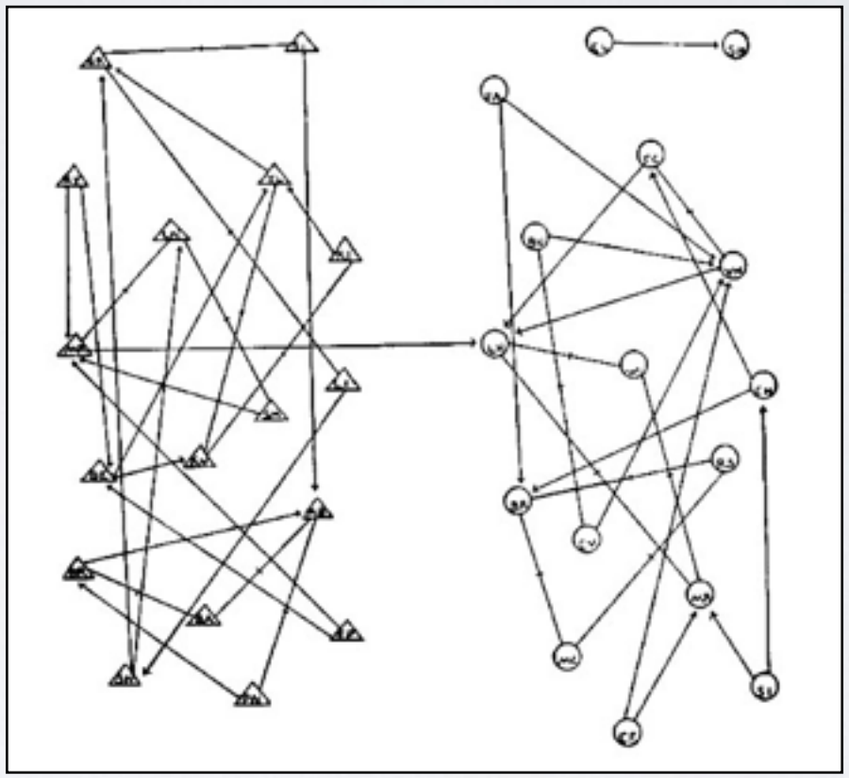
Social networks: mapping structure



EMOTIONS MAPPED BY NEW GEOGRAPHY

Charts Seek to Portray the Psychological Currents of Human Relationships.

FIRST STUDIES EXHIBITED

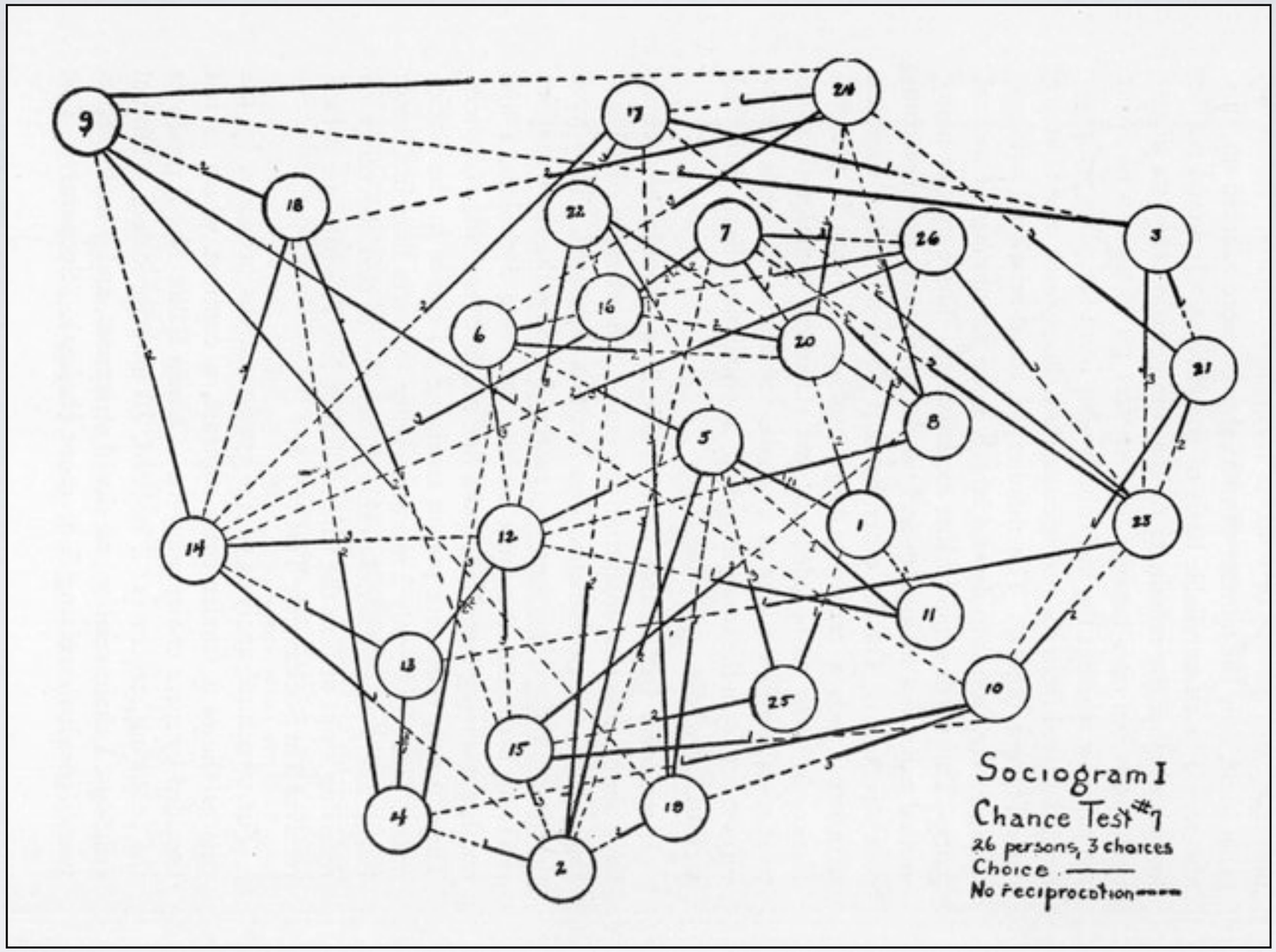


n=33

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."

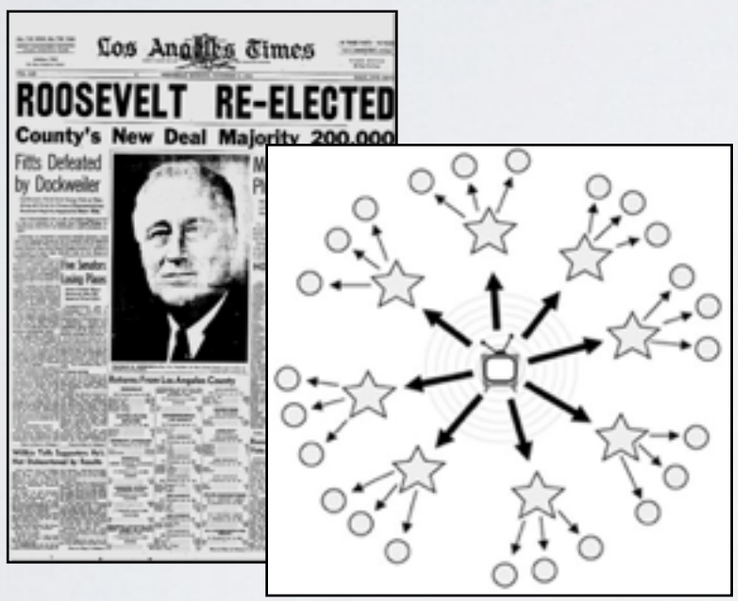
The digital microscope

n>1,400,000,000

“The emergence of ‘cyberspace’ and the World Wide Web is like the discovery of a new continent.” – Jim Gray, 1998 Turing Award address

Processes on social networks

1940 election:
two-step theory of opinion leaders

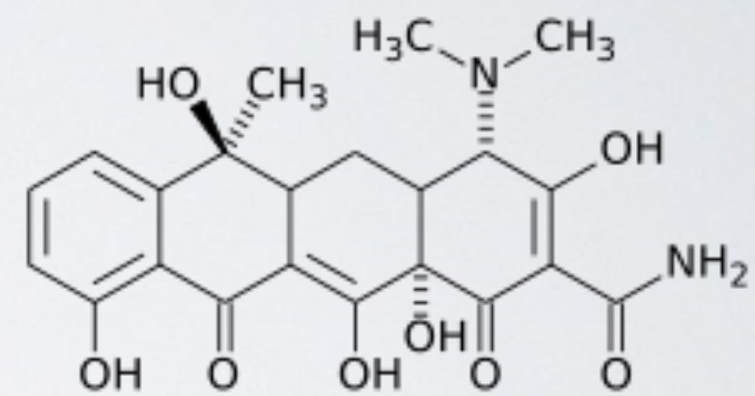


Lazarsfeld et al. '55
Watts-Dodds '07

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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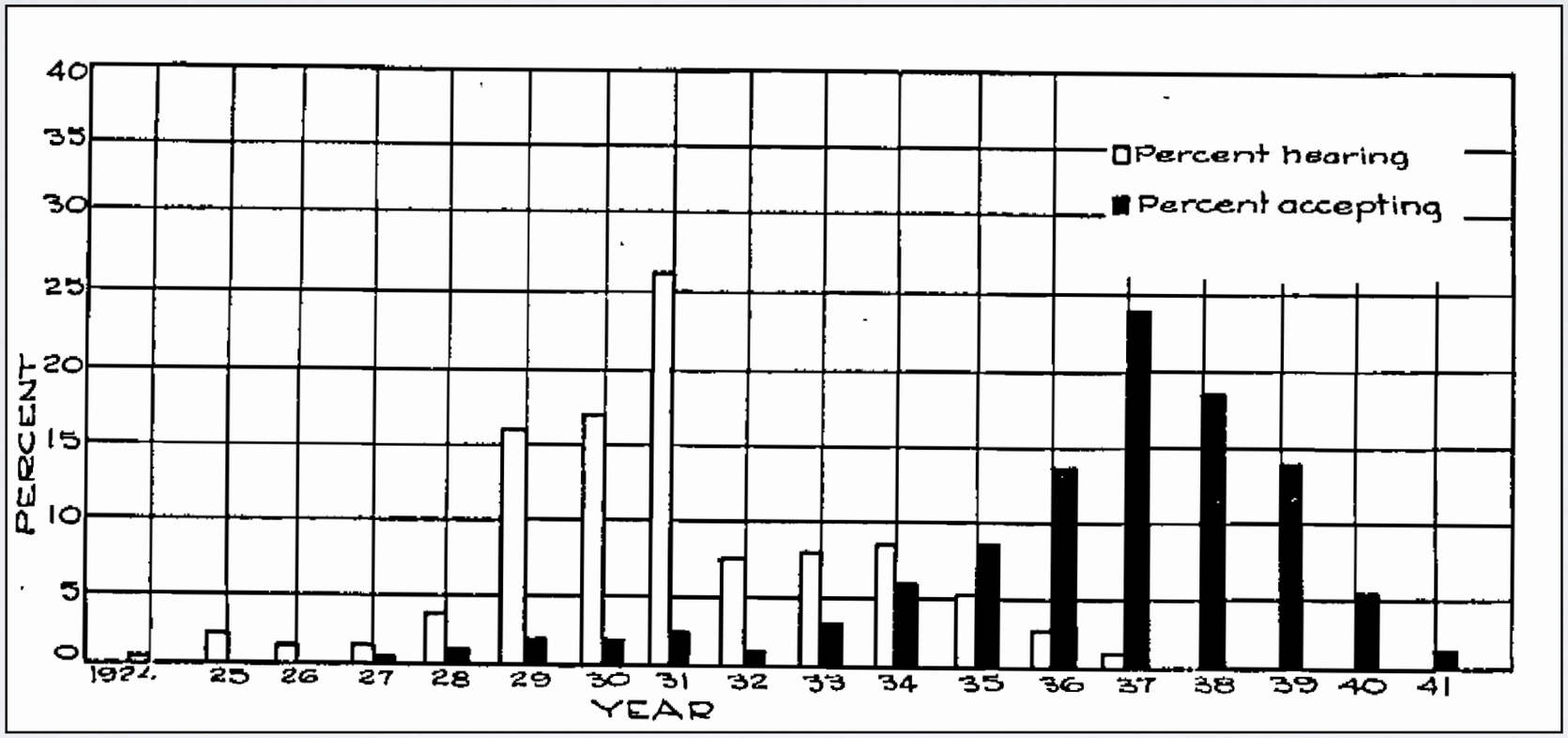
Processes on social networks

Hybrid seed corn (Ryan-Gross):

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



Survey of n=259 farmers

- B Ryan, N Gross (1943) “The diffusion of hybrid seed corn in two Iowa communities”, Rural sociology.
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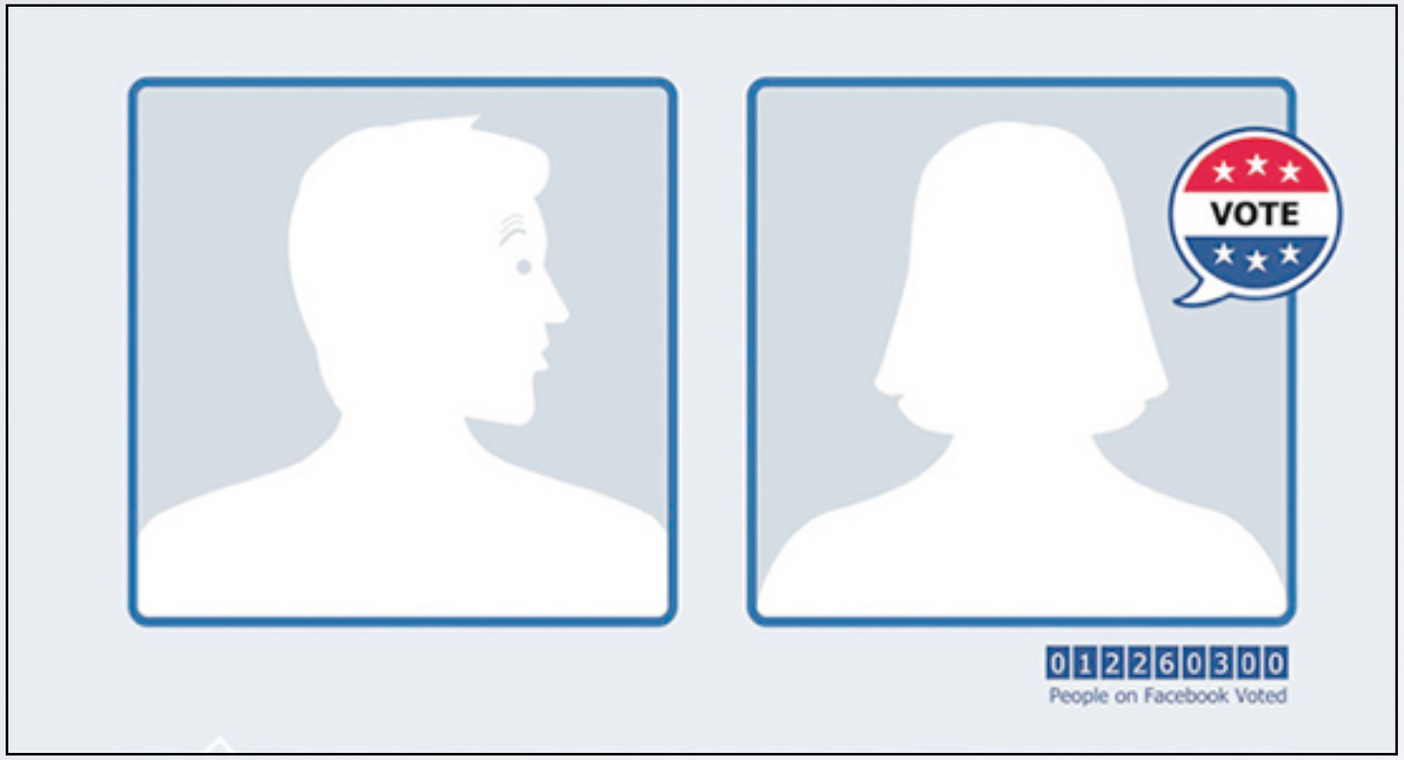
Digital experimental microscope

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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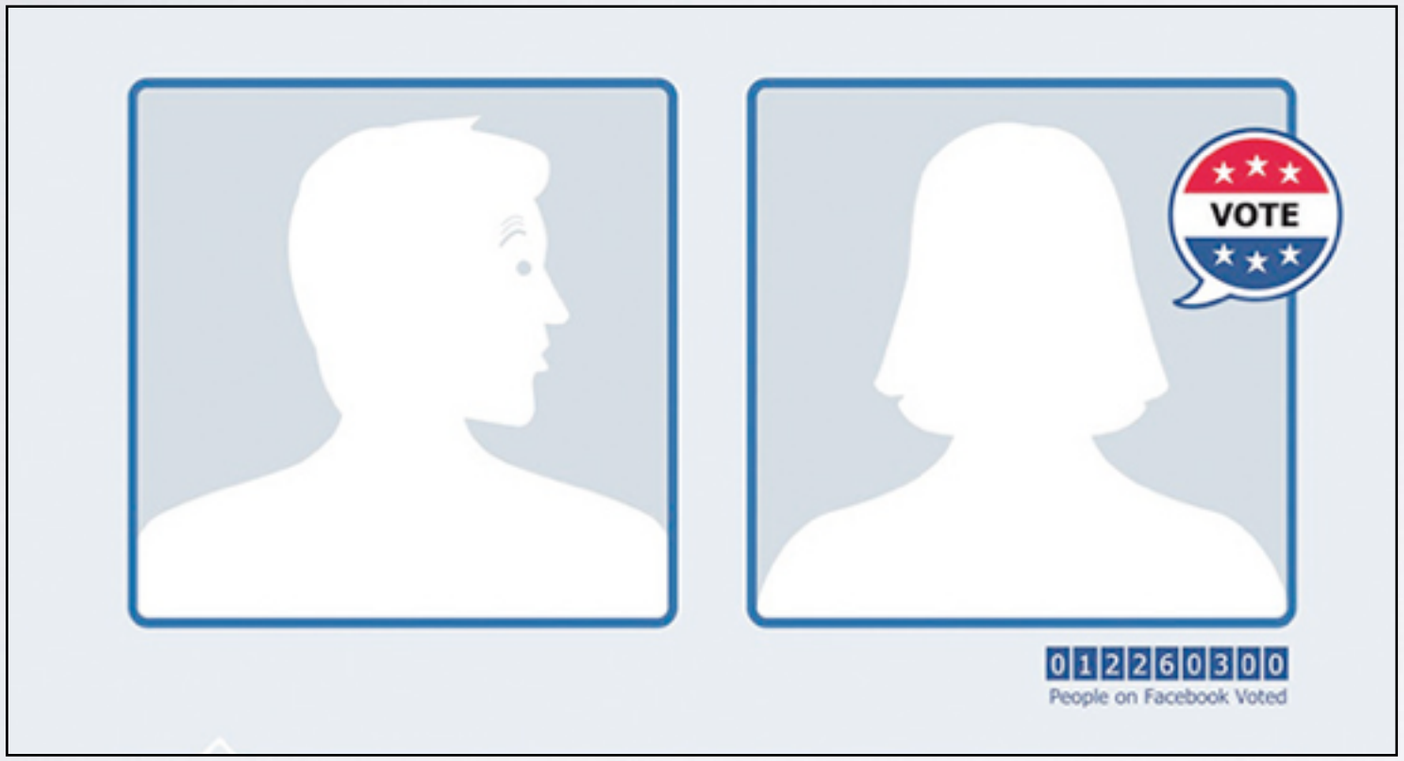

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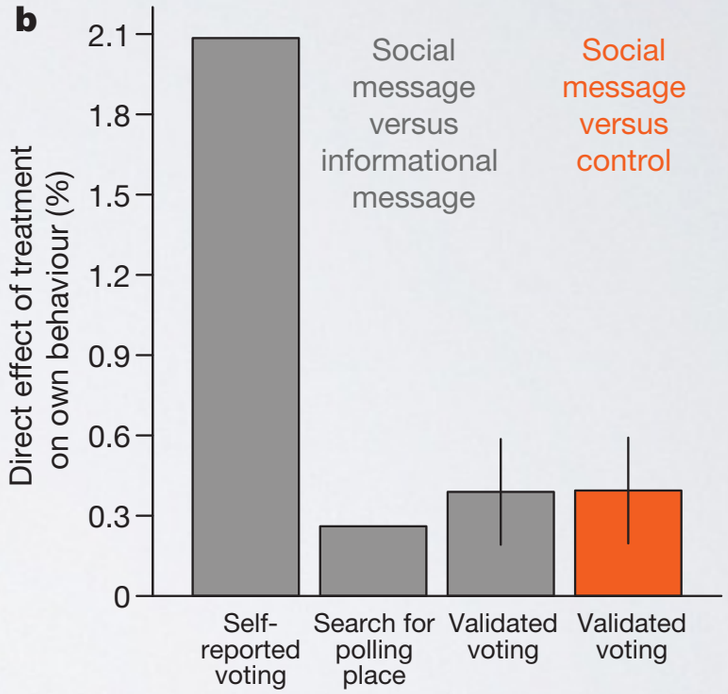

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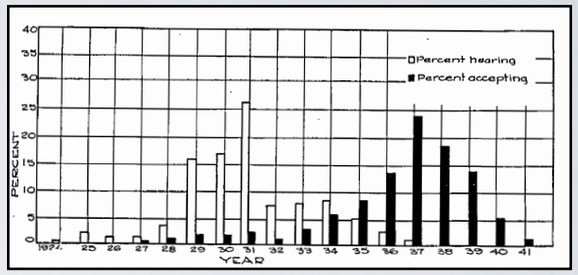
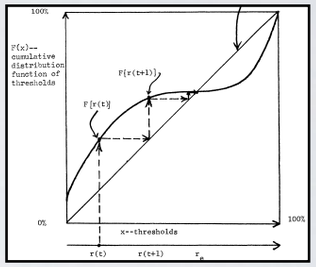
Timeline

- 1940s–50s: Early theories, early data

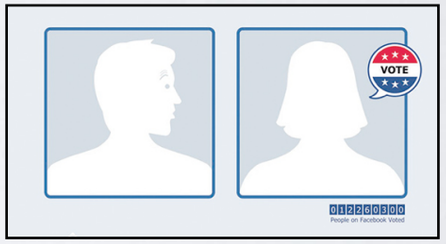


- 1960s–90s: Theory refinement/testing



- 2000s: Large-scale data

- 2010s: Large-scale experiments



Designing/analyzing experiments to develop/test network theories

= Big opportunity

Outline of this tutorial

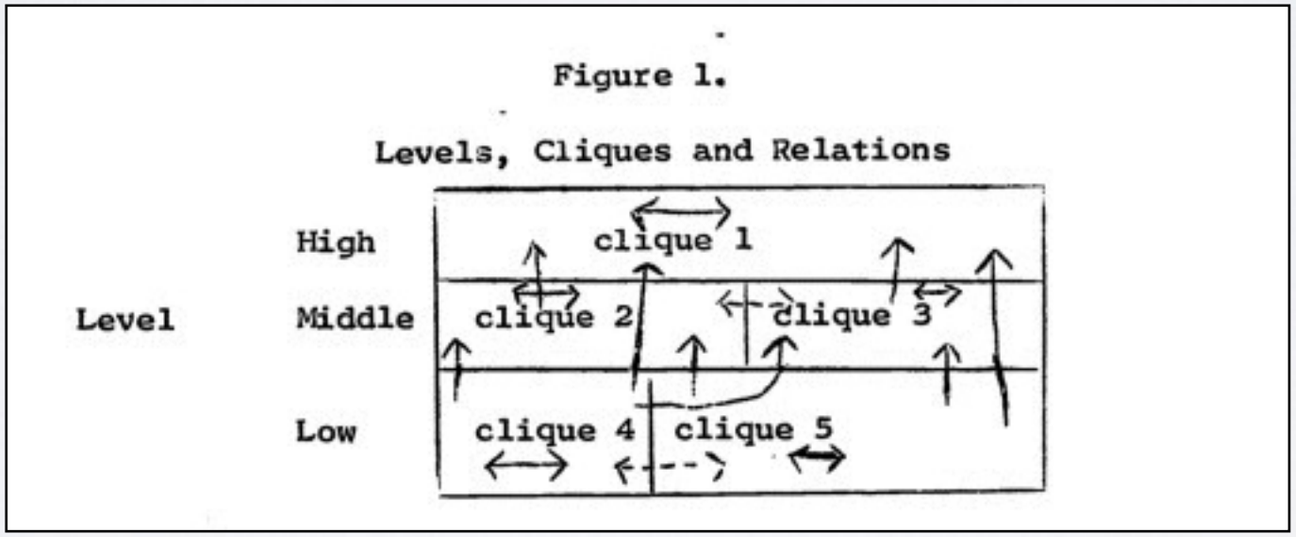
- Part I: From Theory to Data (9:00–10:00)
    - What network?
    - From karate to communities
    - Influence, instrumented
- Short Break (very short)
- Part II: Experimentation and Causal Inference (10:05–11:00)
    - Homophily vs. contagion
    - Influence experiments
    - Network experiments

Part I: from Theory to Data

Testing a theory with data

- Homans (1950): Small groups of people create a social structure that contains many clique subgroups and a ranking system.

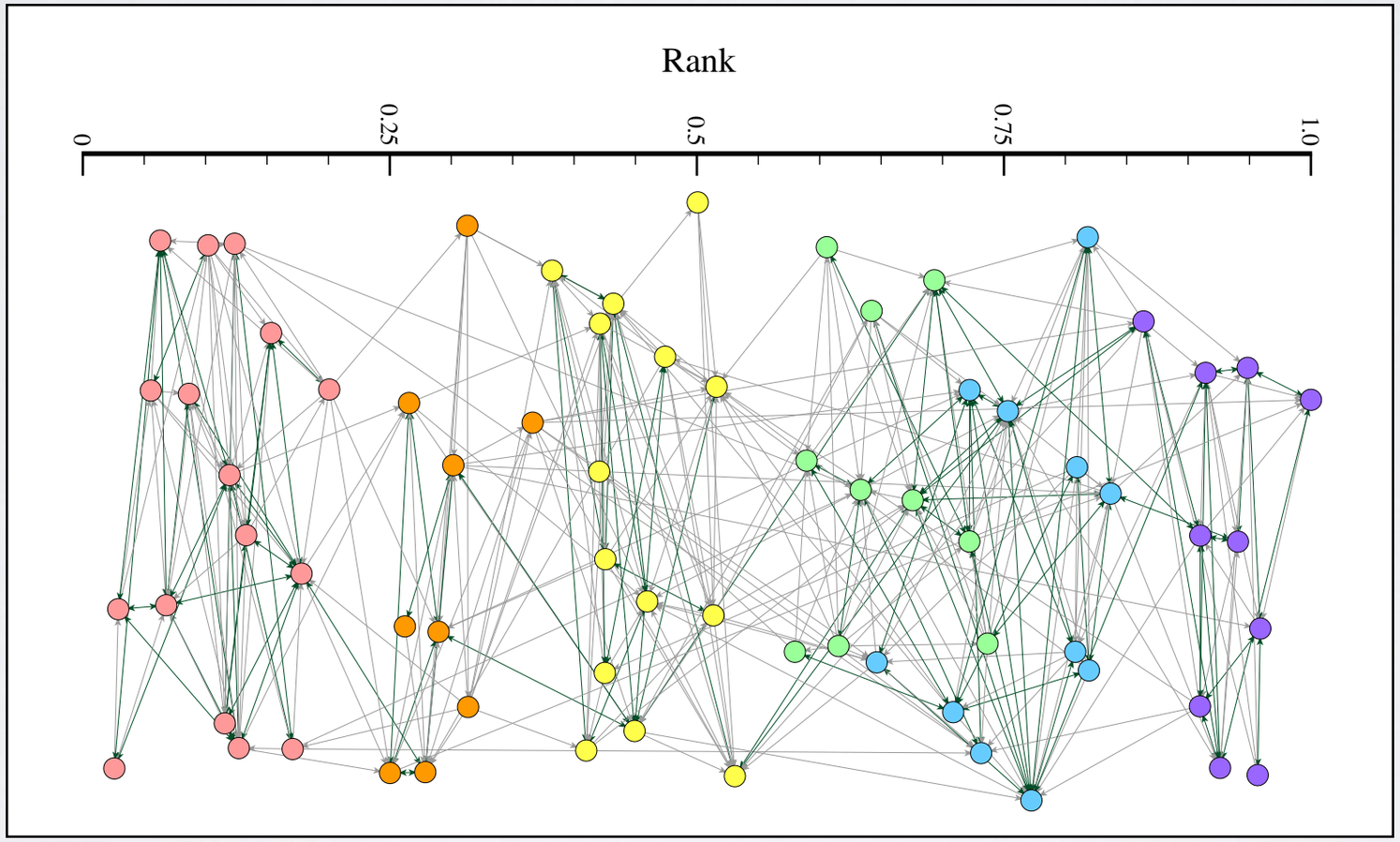
- Davis & Leinhardt (1967): Operational statement using subgraph frequencies: 7 triads less frequent than random model predicts.



- 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.



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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?"

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

"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

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Acquaintances, often international. Business and personal.

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

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Close friends who exercise.

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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
- …

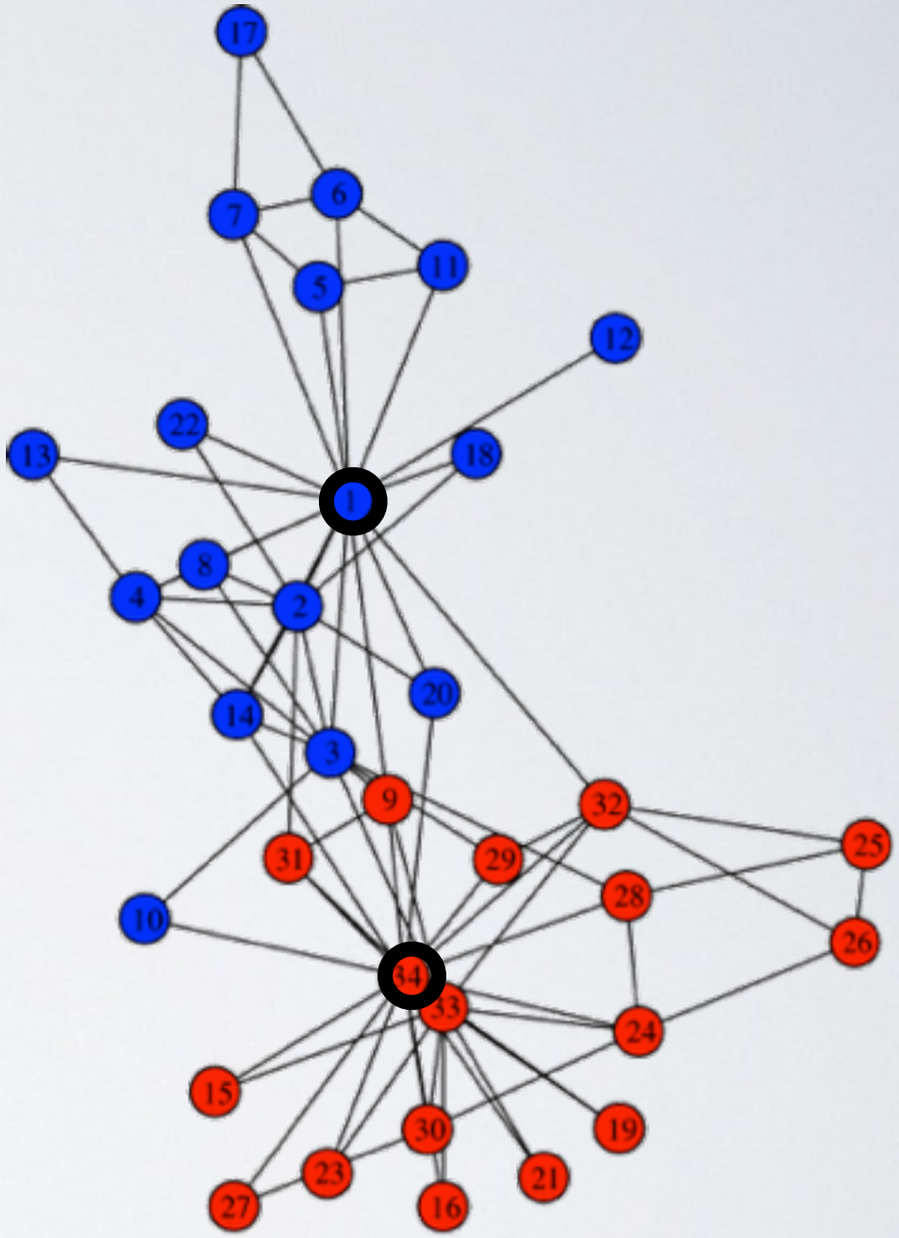
- JP Onnela et al. (2007) "Structure and tie strengths in mobile communication networks," PNAS.
- AZ Jacobs, SF Way, J Ugander, A Clauset (2015) "Assembling thefacebook: Using Heterogeneity to Understand Online Social Network Assembly," WebSci.

Networks: a matter of scale

- 34-node network of a recreational karate club [Zachary 1978]
- 4436-node network of email exchange over 3-months at corporate research lab [Adamic-Adar 2003]
- 43,553-node network of email exchange over 2 years at a large university [Kossinets-Watts 2006]
- 4.4-million-node network of declared friendships on a blogging community [Liben-Nowell et al. 2005, Backstrom et al. 2006]
- 240-million-node network of all IM communication over a month on Microsoft Instant Messenger [Leskovec-Horvitz 2008]
- 721-million-node network of Facebook friendships between all active users in May 2011 [Ugander et al. 2011]
- 1.44-billion-node network of Facebook monthly active users in March 2015.

Zachary Karate Club

- Wayne Zachary, sociologist interested in group dynamics.
- 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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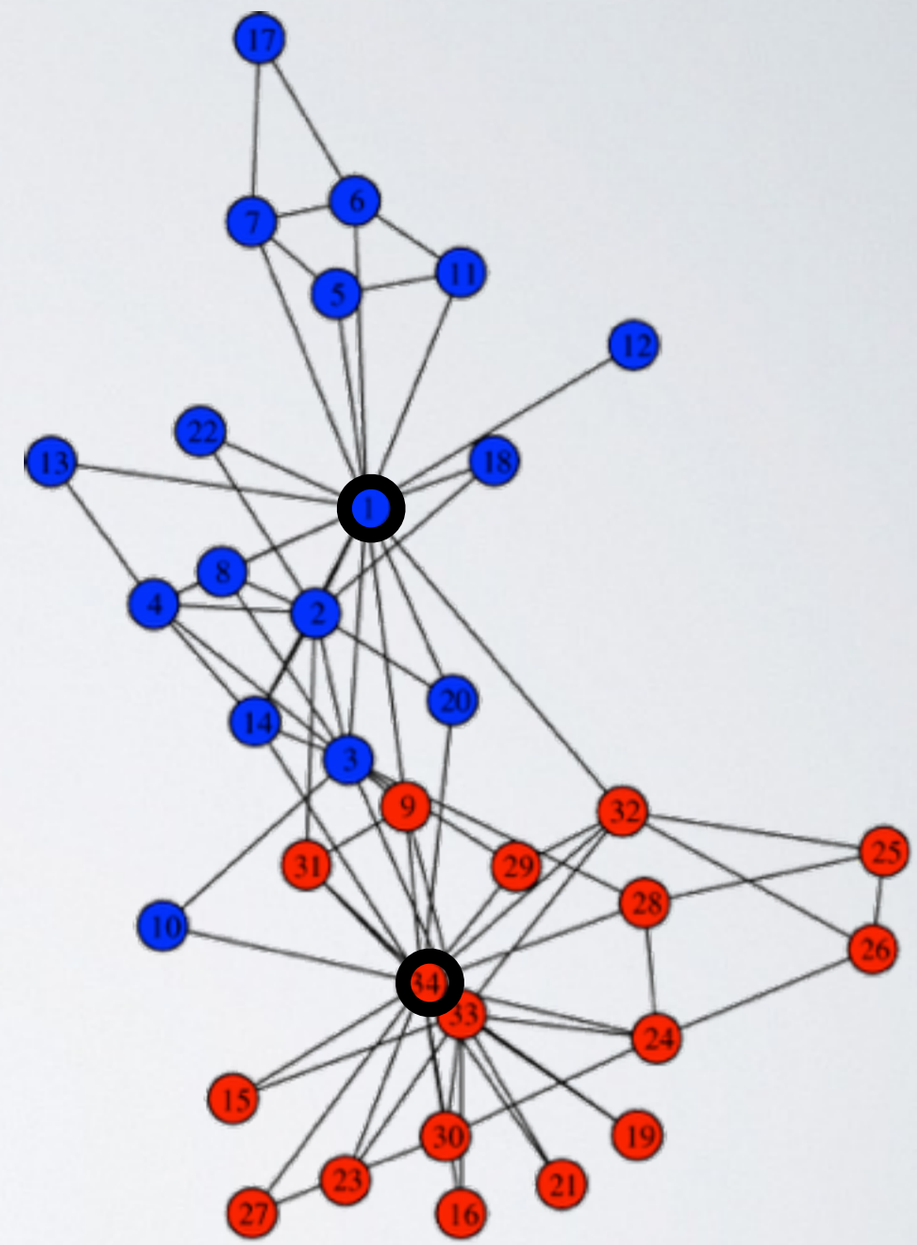
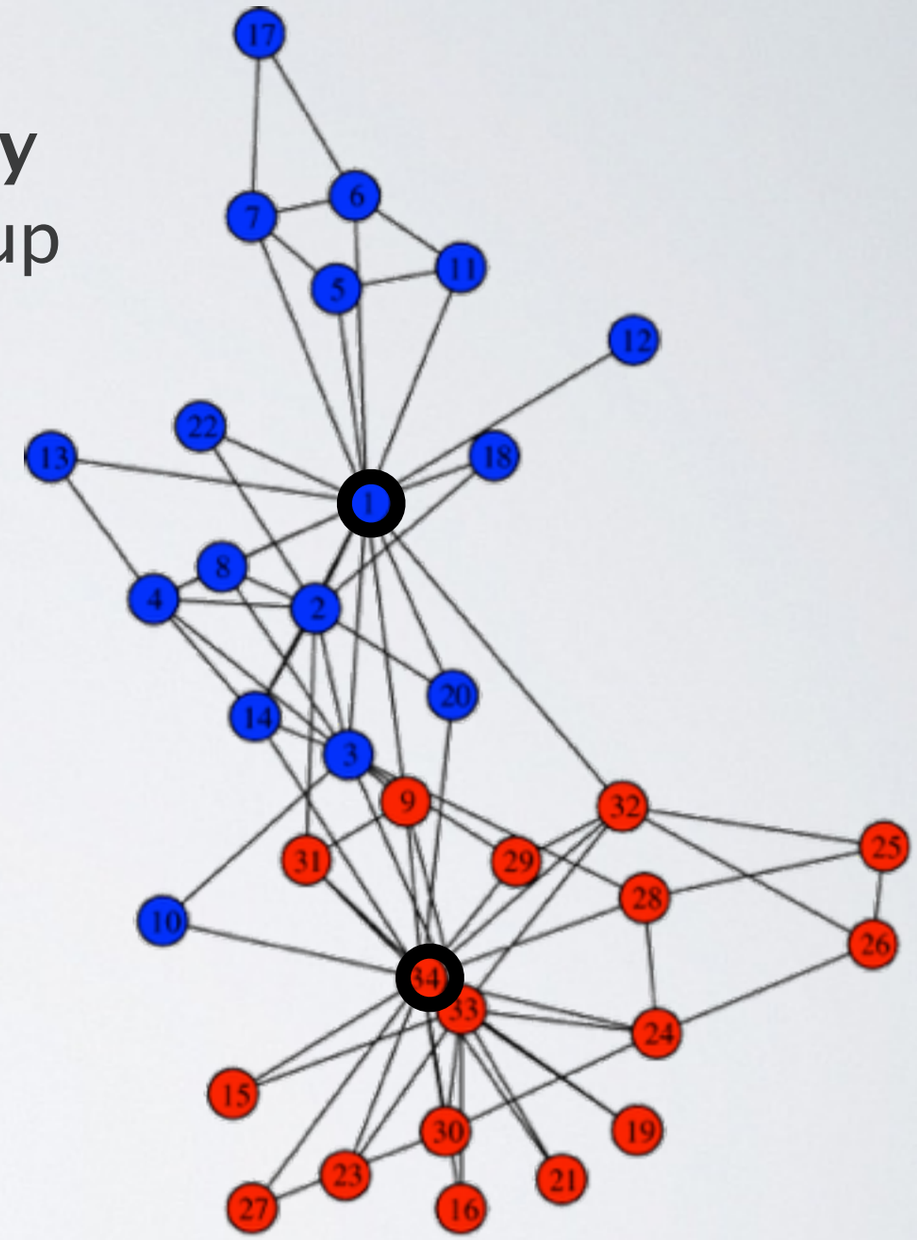
- **Network Flow!** Applied Ford–Fulkerson, found group split was predicted by min–cut.



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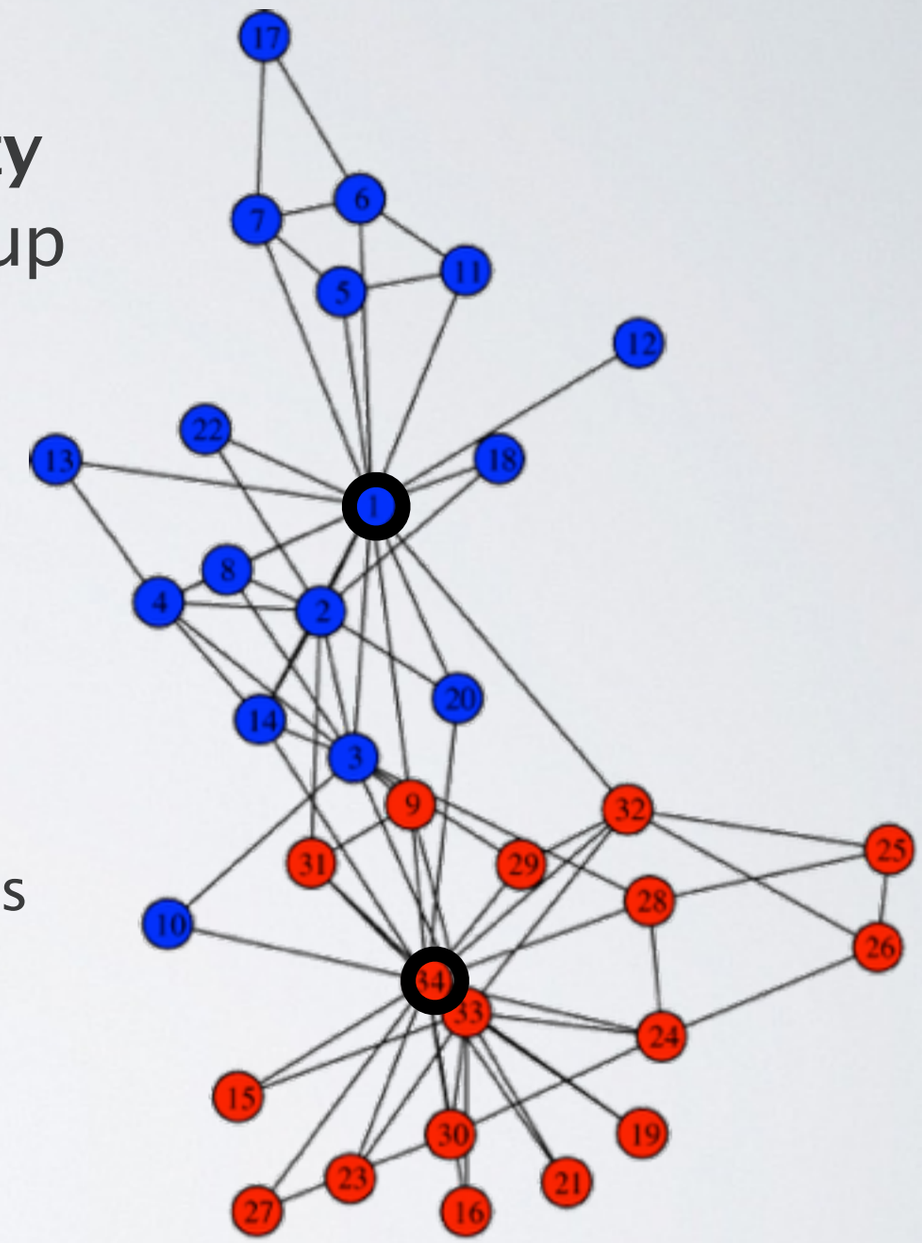
- Other objectives
  - Modularity maximization:
    - Has "resolution limit"
  - Conductance (normalized min-cut):
    - Produces balanced partitions; spectral guarantees



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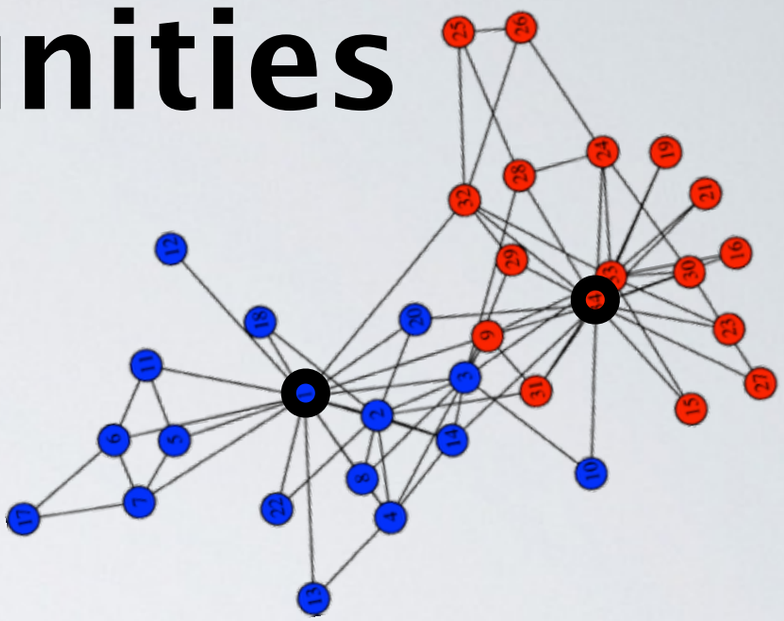

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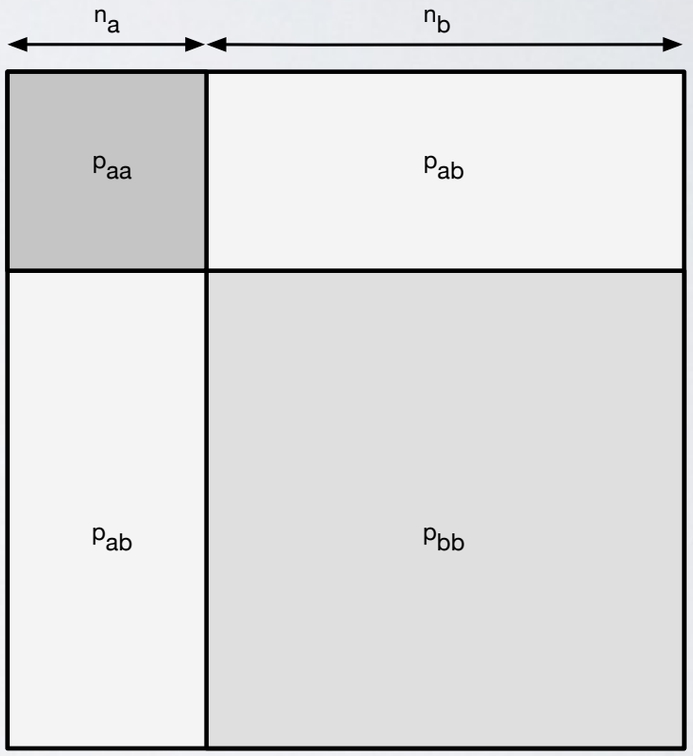
  - Ability to recover Stochastic Block Model:
    - Stylized model in absence of ground truth data



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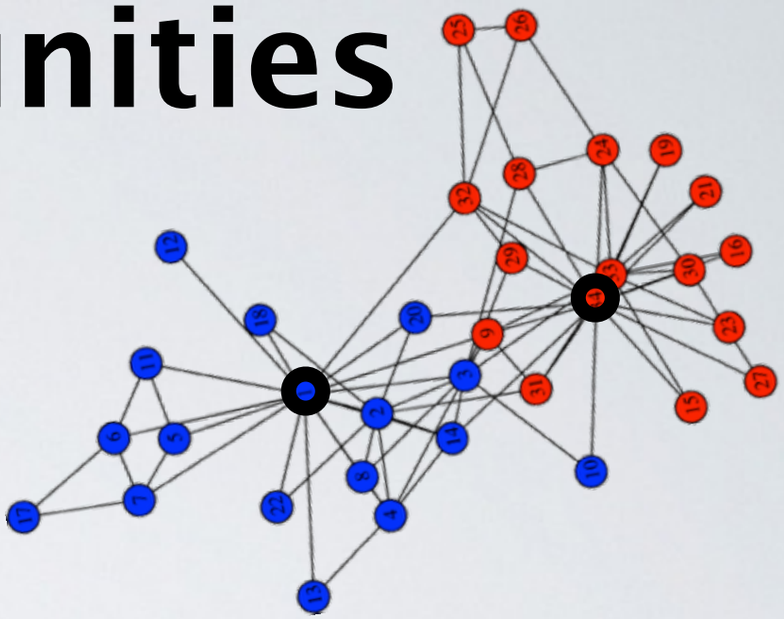

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  - Ability to recover Stochastic Block Model:
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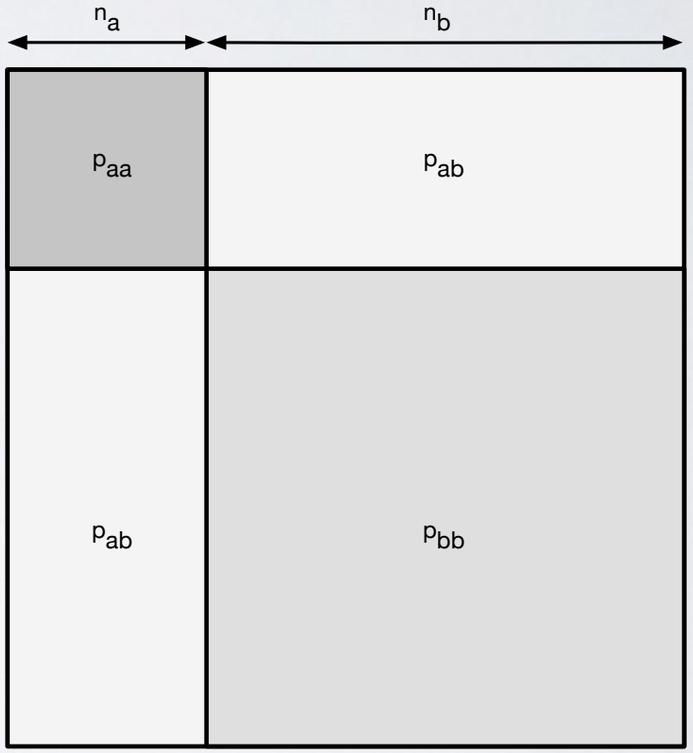
  - Variance in clustered network experiments?



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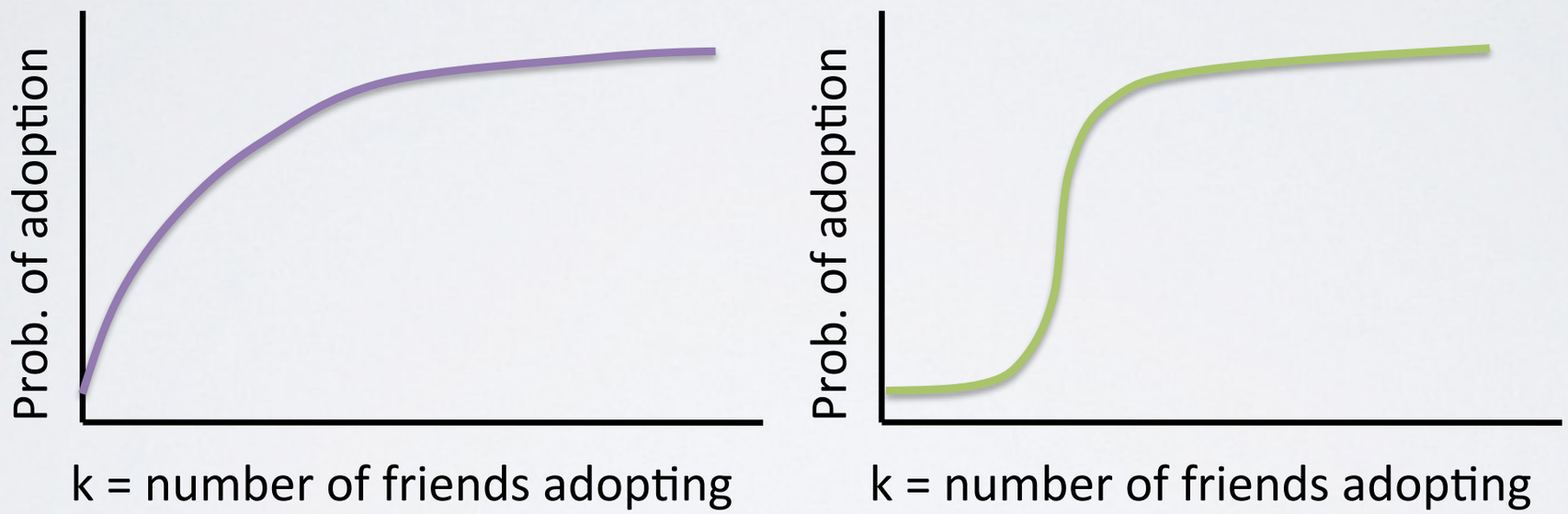
Influence, instrumented

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



- F Bass (1969) "A new product growth for model consumer durables". Management Science.
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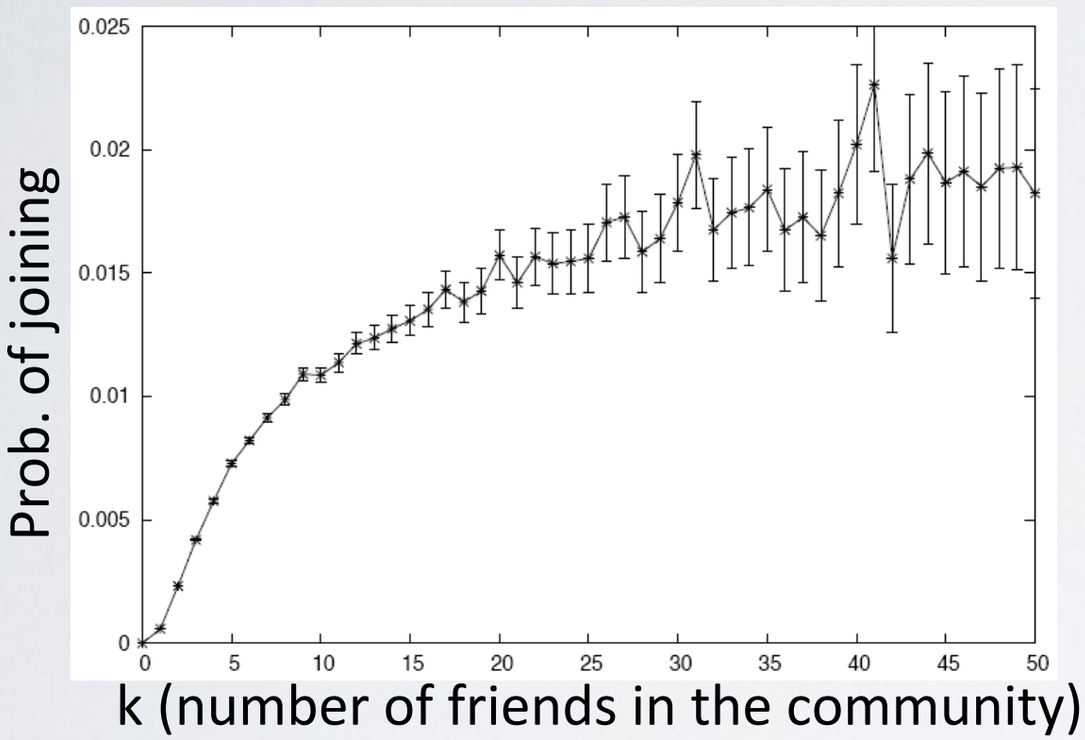
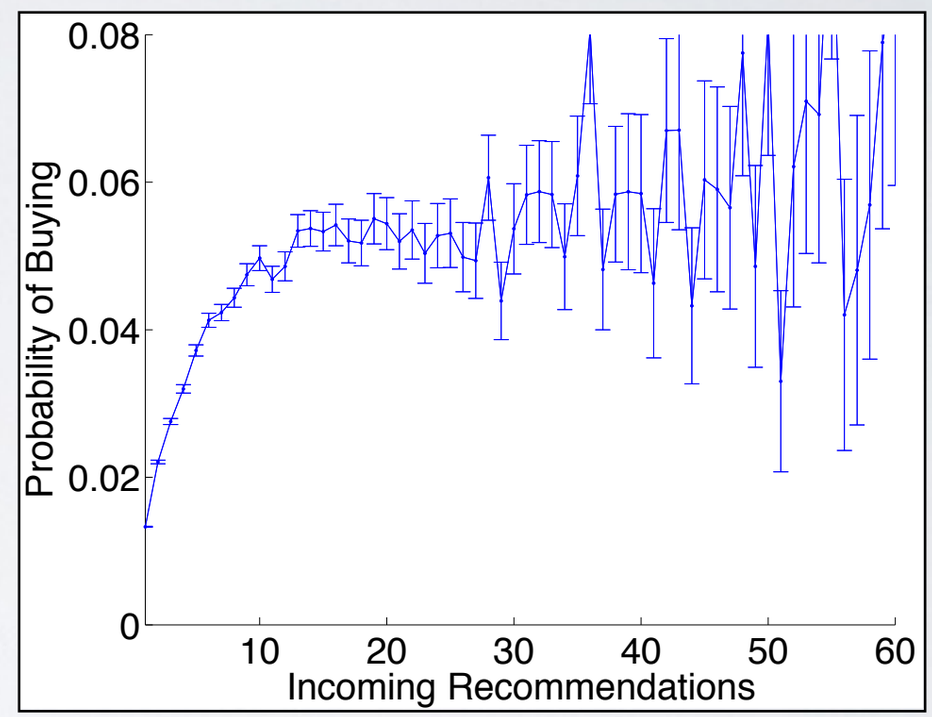
Influence, instrumented

Backstrom et al. 2006: Probability of joining LiveJournal group



Leskovec et al. 2006: Probability of buying a DVD



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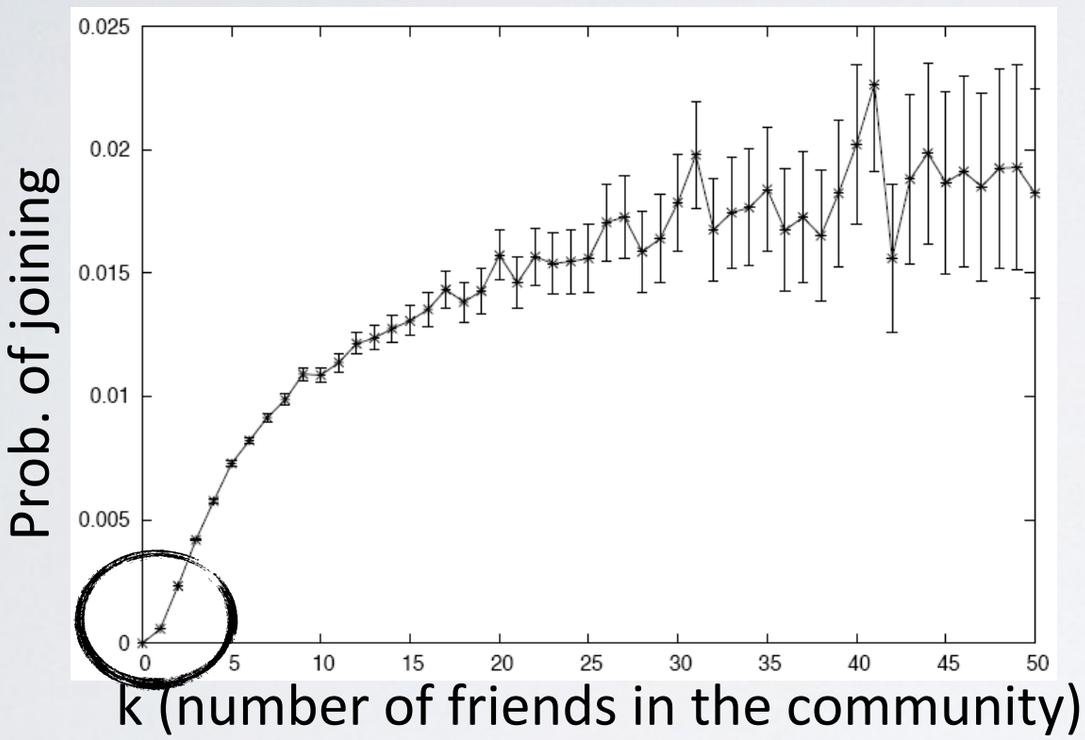

Complex contagion?

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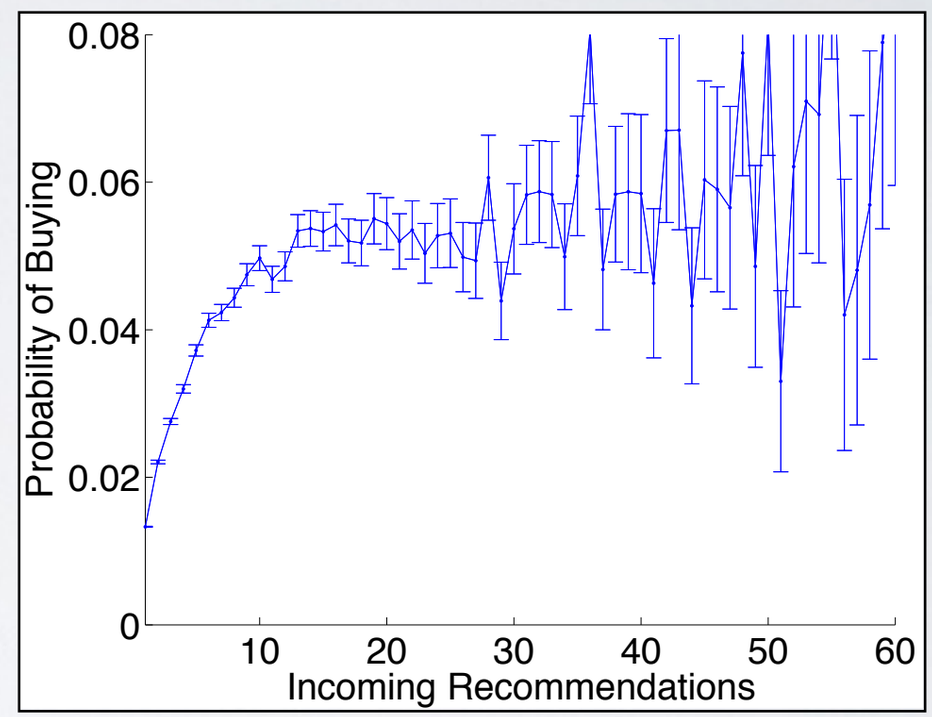

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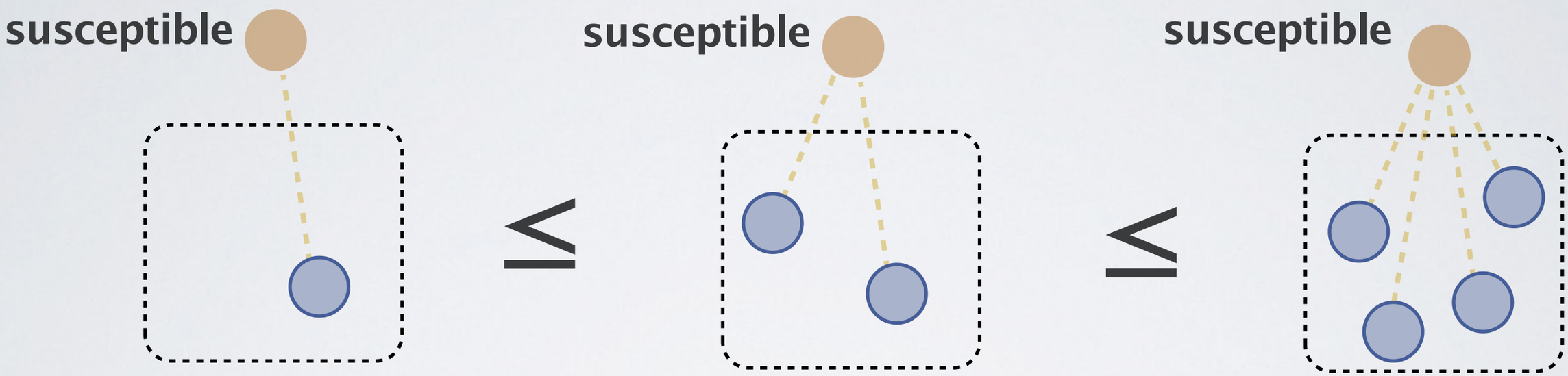
Influence and graph structure

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



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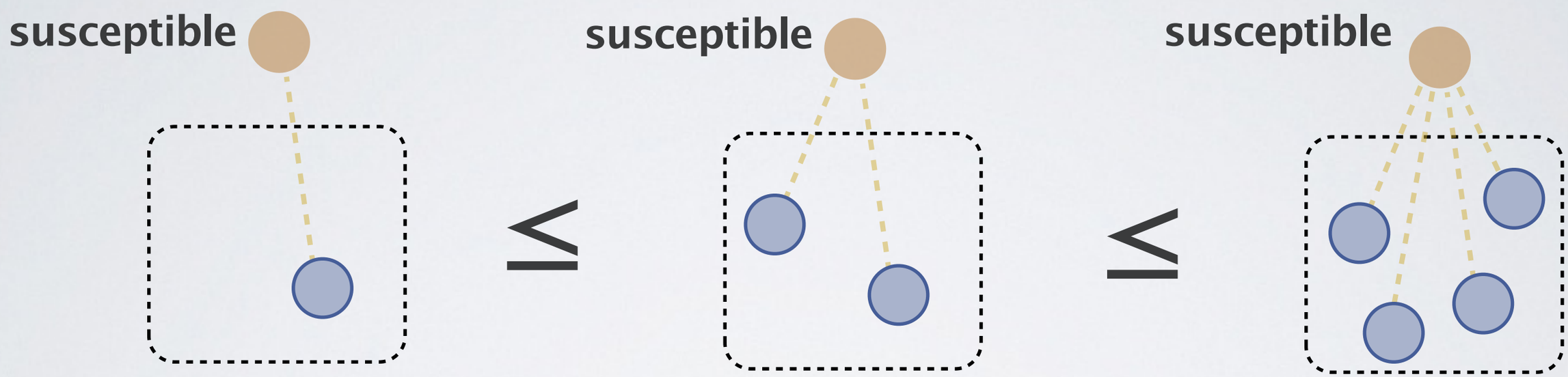

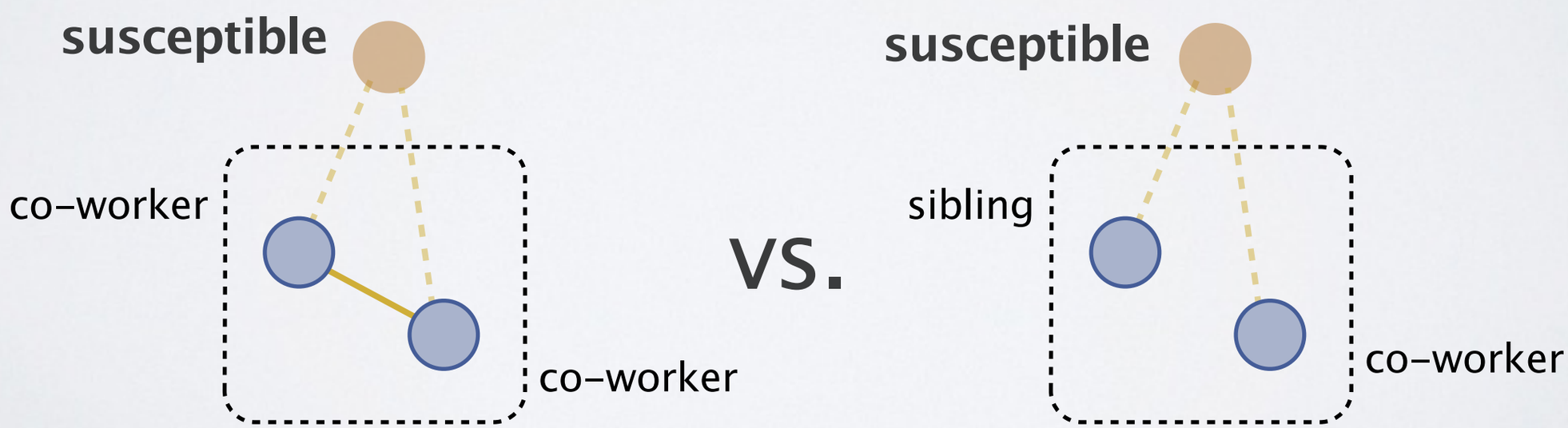

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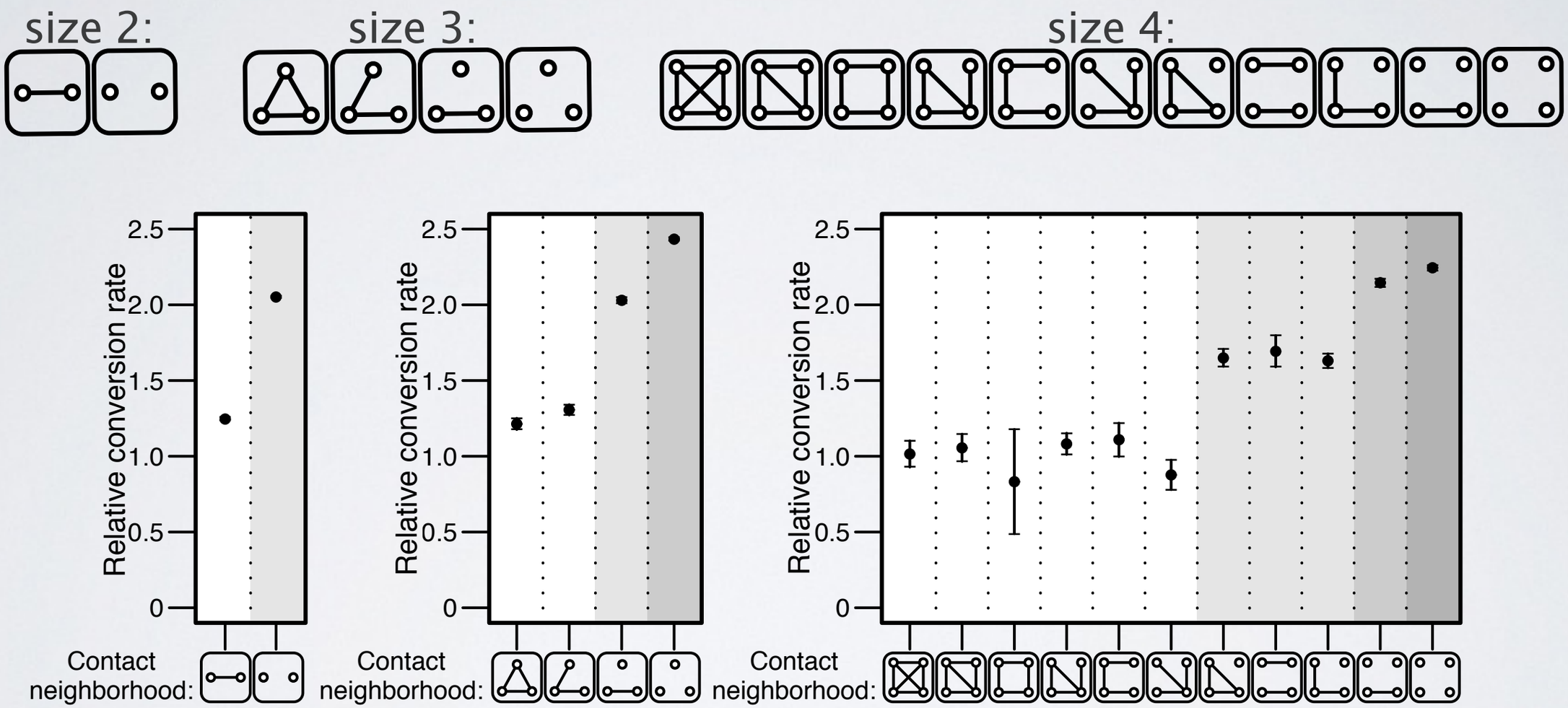
Structural diversity

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

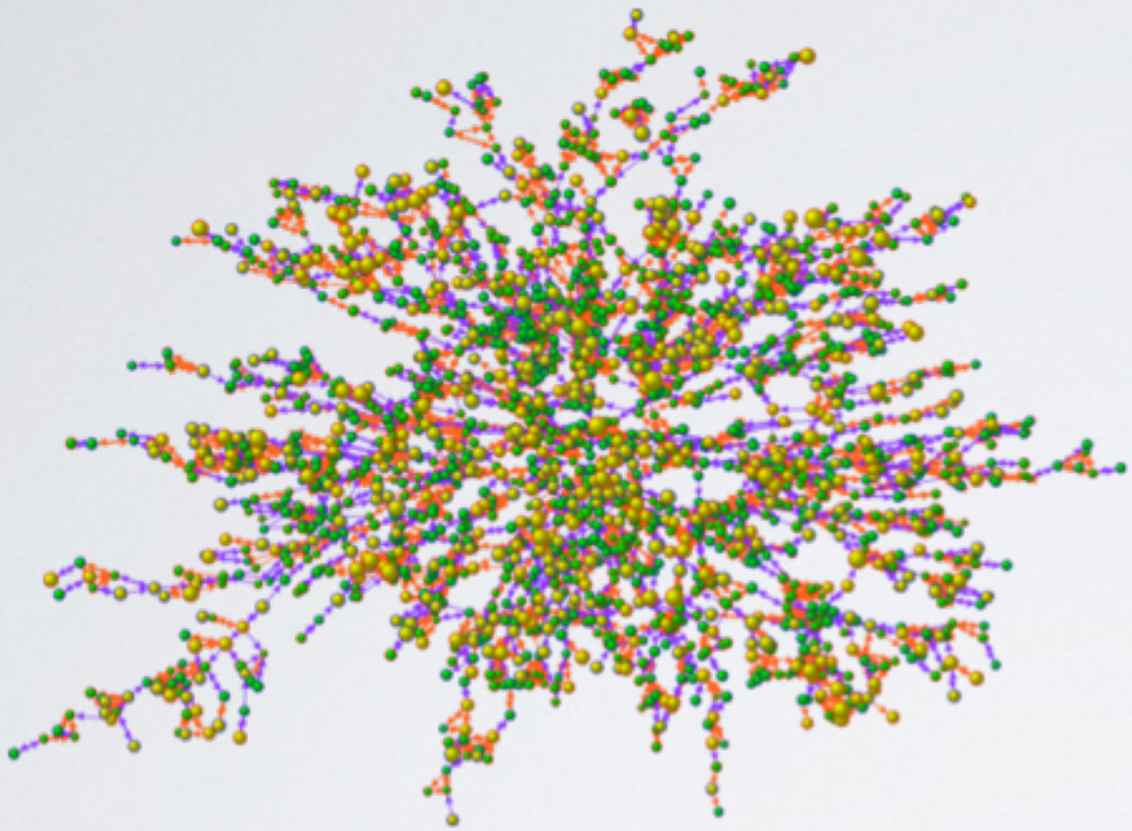


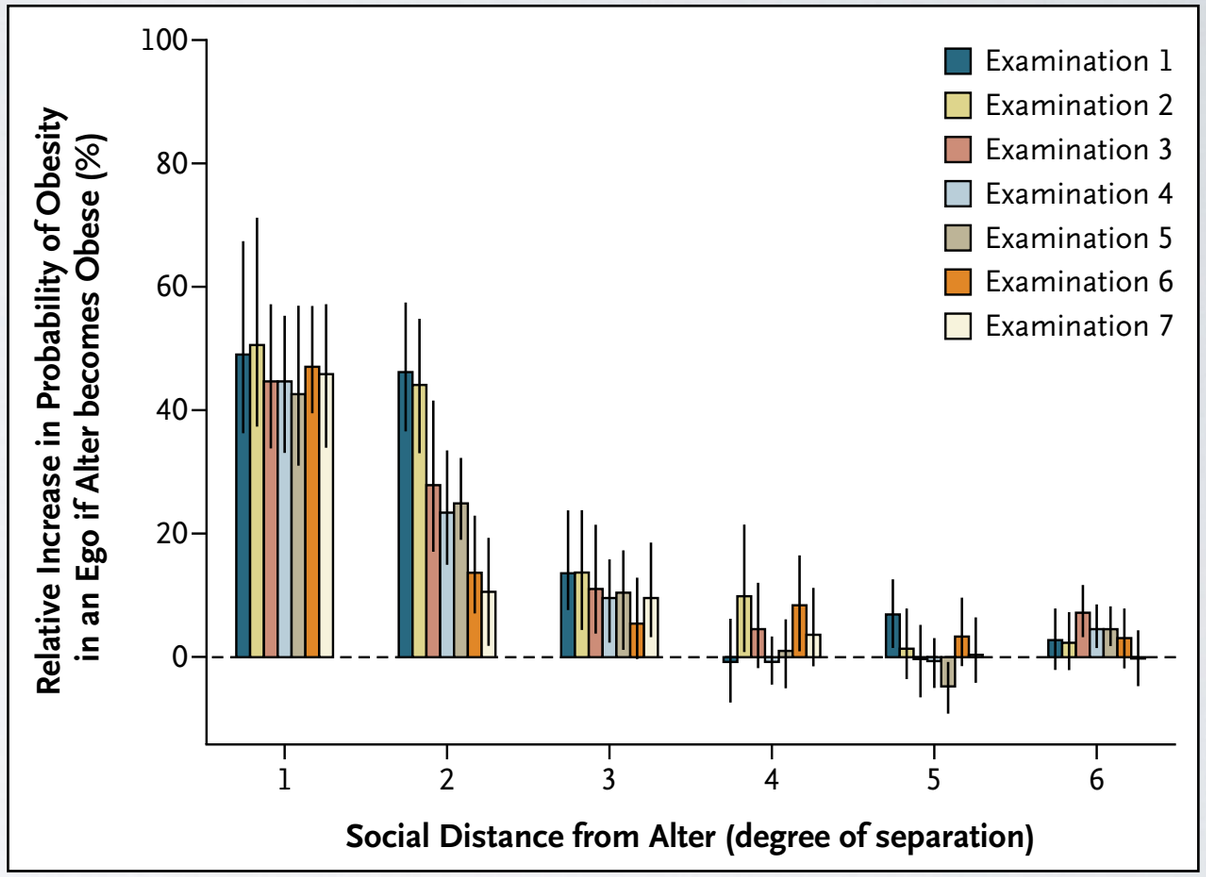
- J Ugander, L Backstrom, C Marlow, J Kleinberg (2012) “Structural diversity in social contagion,” PNAS.

Part II: Experimentation and Causal Inference

http://www.stanford.edu/~jugander/ec-tutorial/

Is obesity contagious?

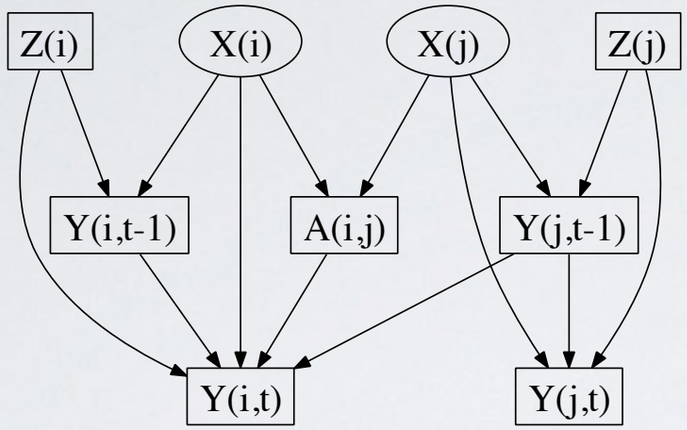




"comparing the conditional probability of obesity in the observed network with the probability of obesity in identical networks (with topology preserved) in which the same number of obese persons is randomly distributed"

- 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

- N Christakis, J Fowler (2007) "The Spread of Obesity in a Large Social Network over 32 Years," New England J of Medicine.
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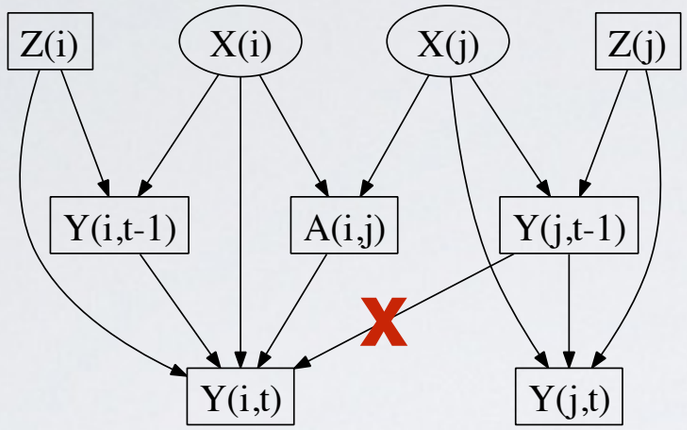

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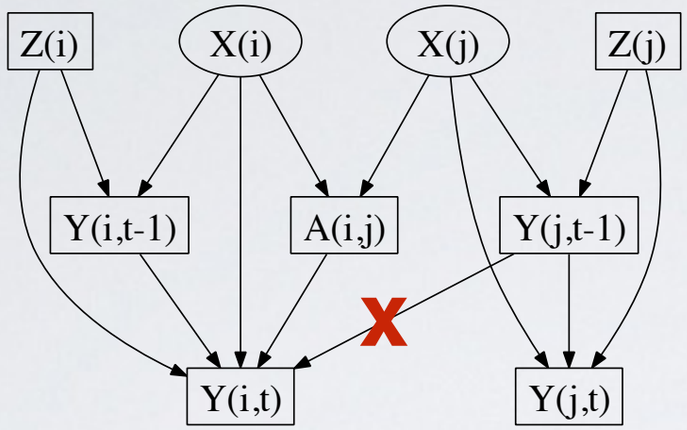

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"Feed Condition"

"No Feed Condition"

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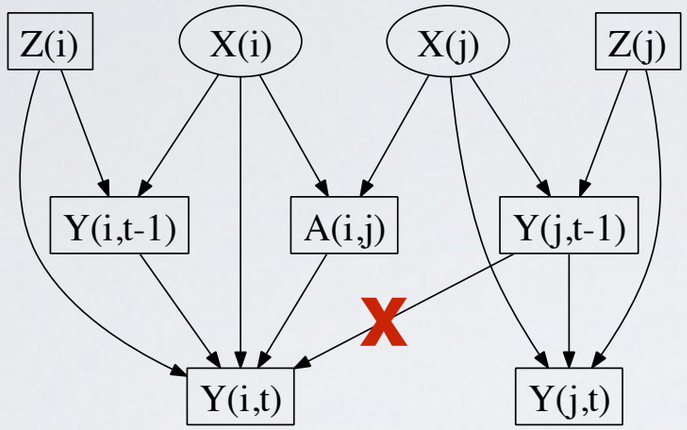
Knock-out experiments



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

"Feed Condition"

"No Feed Condition"

Feed condition:

7.37x

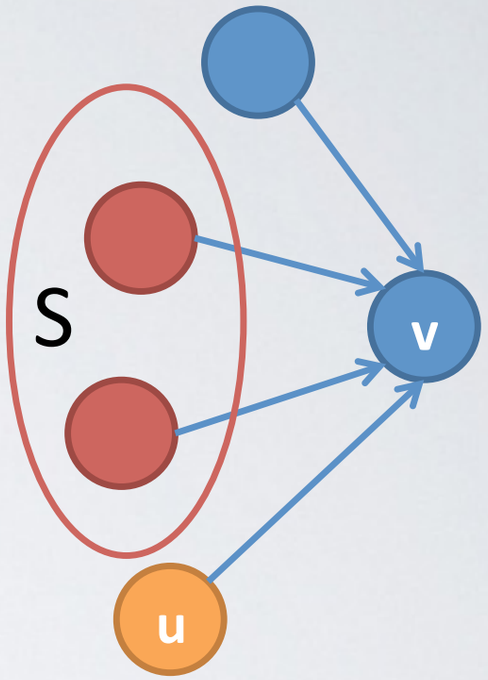
more likely to share.

- 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.
- E Bakshy et al. (2012) "The Role of Social Networks in Information Diffusion," WWW.

Influence maximization

General model (Kempe et al. 2003):

- When **u** tries to influence **v**: success based on set of nodes **S** that already tried & failed
- Success functions $\mathbf{p_v(u,S)}$**:**
  - Independent cascades: $p_v(u,S) = p_{uv}$
  - Threshold: if $|S|=k$: $p_v(u,S)=1$ else 0
  - Diminishing returns: $p_v(u,S) \geq p_v(u,T)$ if S subset of T



Most influential set of size *k*: the set *S* of *k* nodes producing largest expected cascade size *f(S)* if activated.

NP-hard, diminishing returns function yields (1-1/e)-factor approximation.

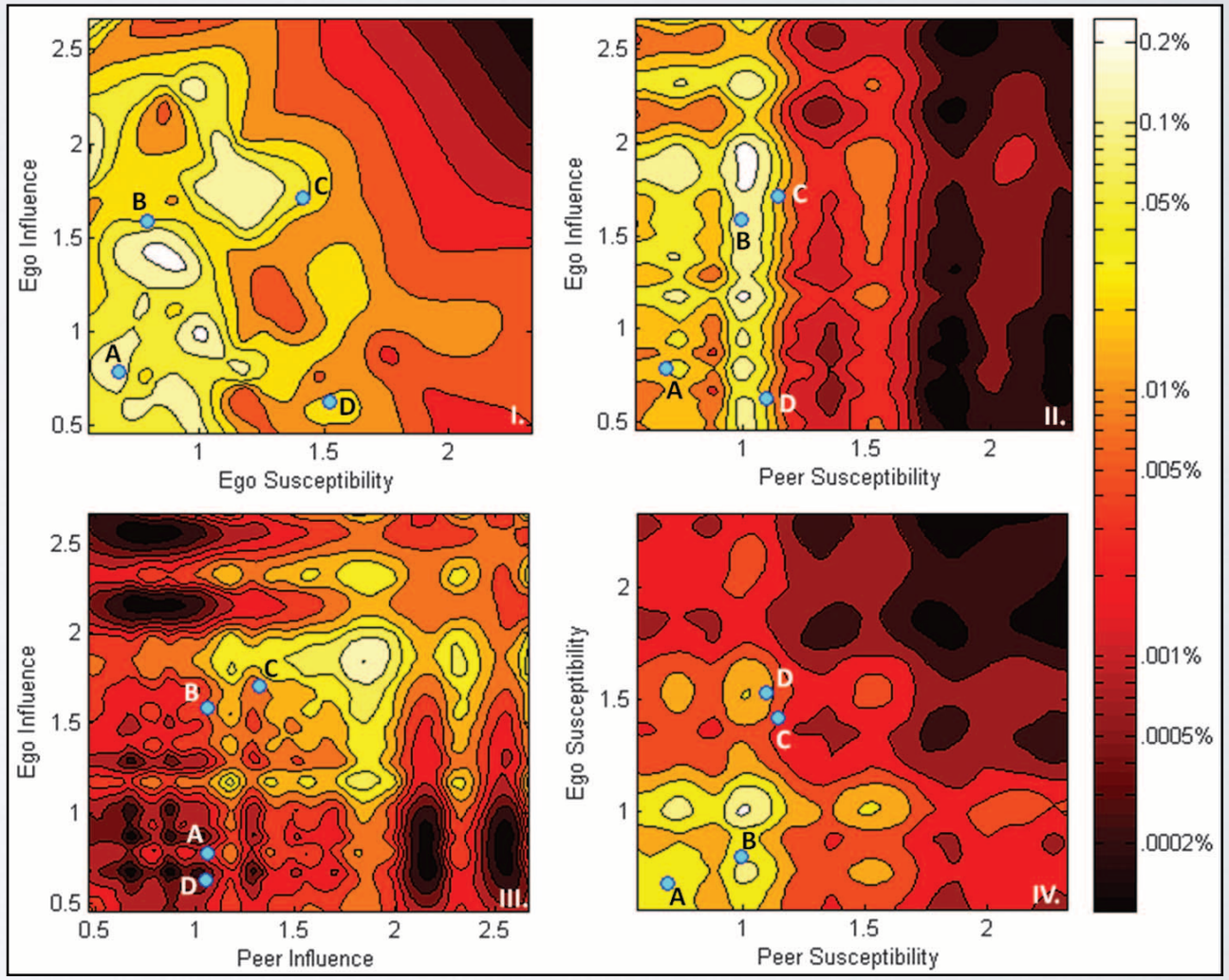
- D Kempe, J Kleinberg, E Tardos (2003) "Maximizing the spread of influence through a social network," KDD.
- J Leskovec et al. (2007) "Cost-effective outbreak detection in networks," KDD.

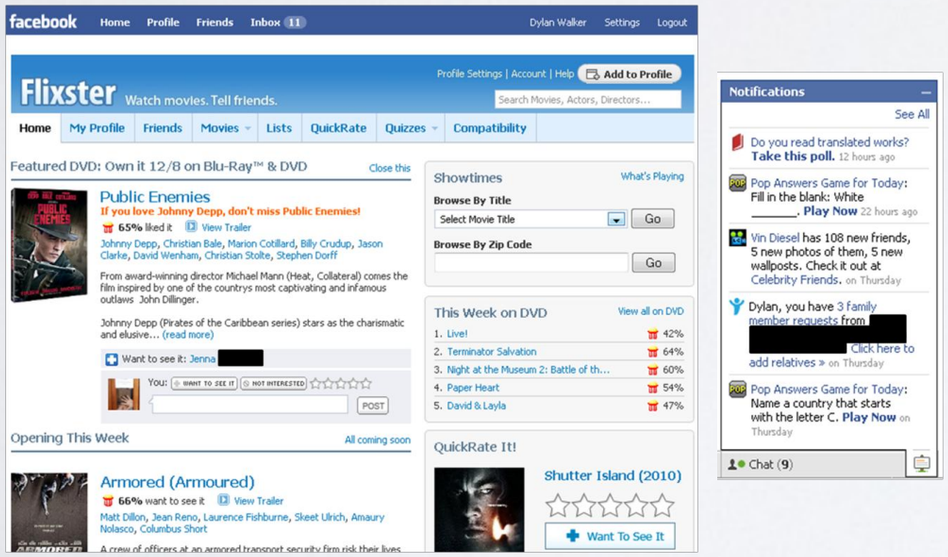
Influence and susceptibility

- (Aral–Walker 2012): Randomized experiment using Facebook “app” for movie recommendations.

- Influence and susceptibility found to be decoupled (here, for movies)

- Many results on traits that correlate with influence/susceptibility.

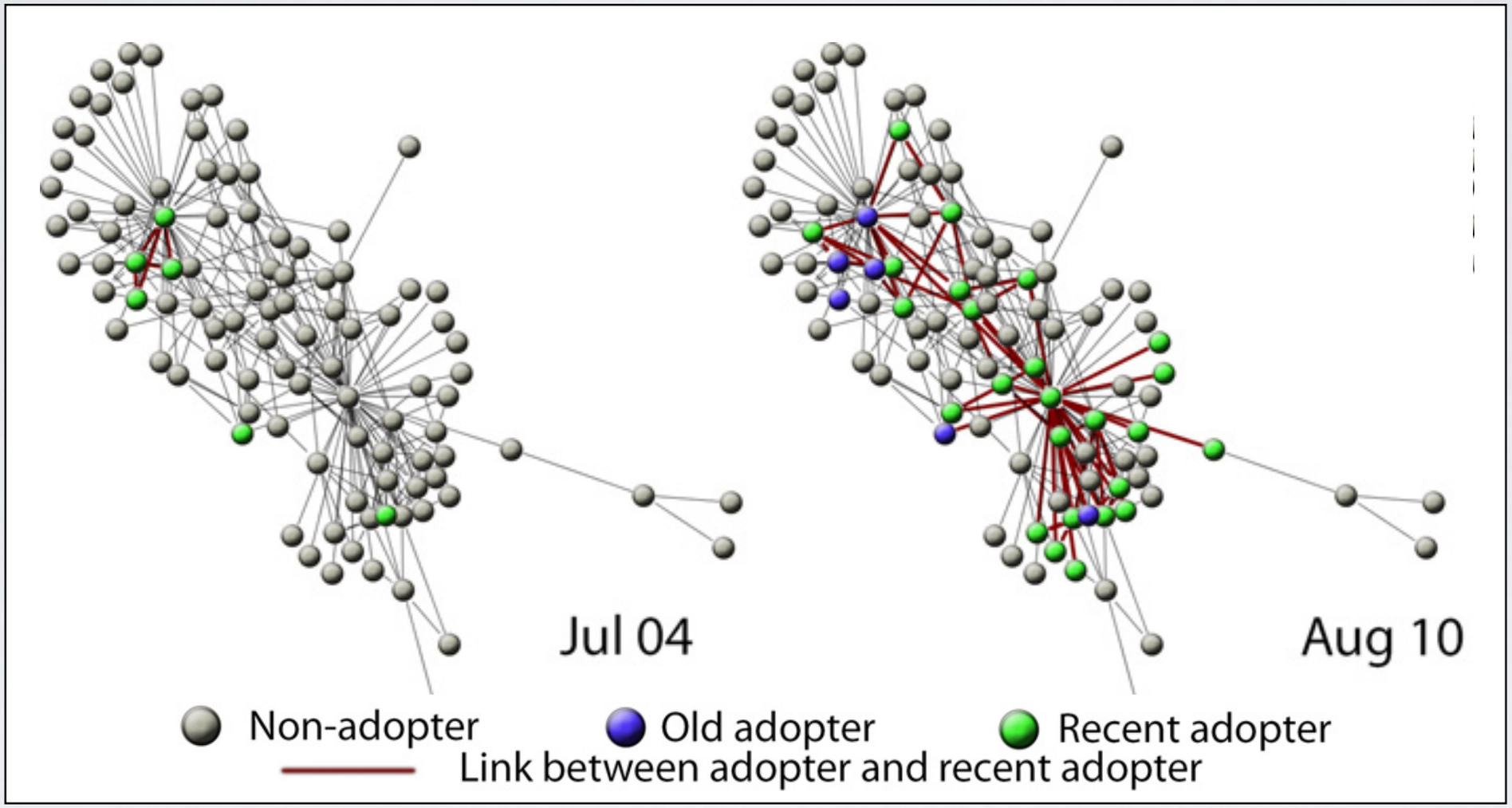




- S Aral, D Walker (2012) "Identifying Influential and Susceptible Members of Social Networks," Science.
- D Centola (2010) "The spread of behavior in an online social network experiment," Science.

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.

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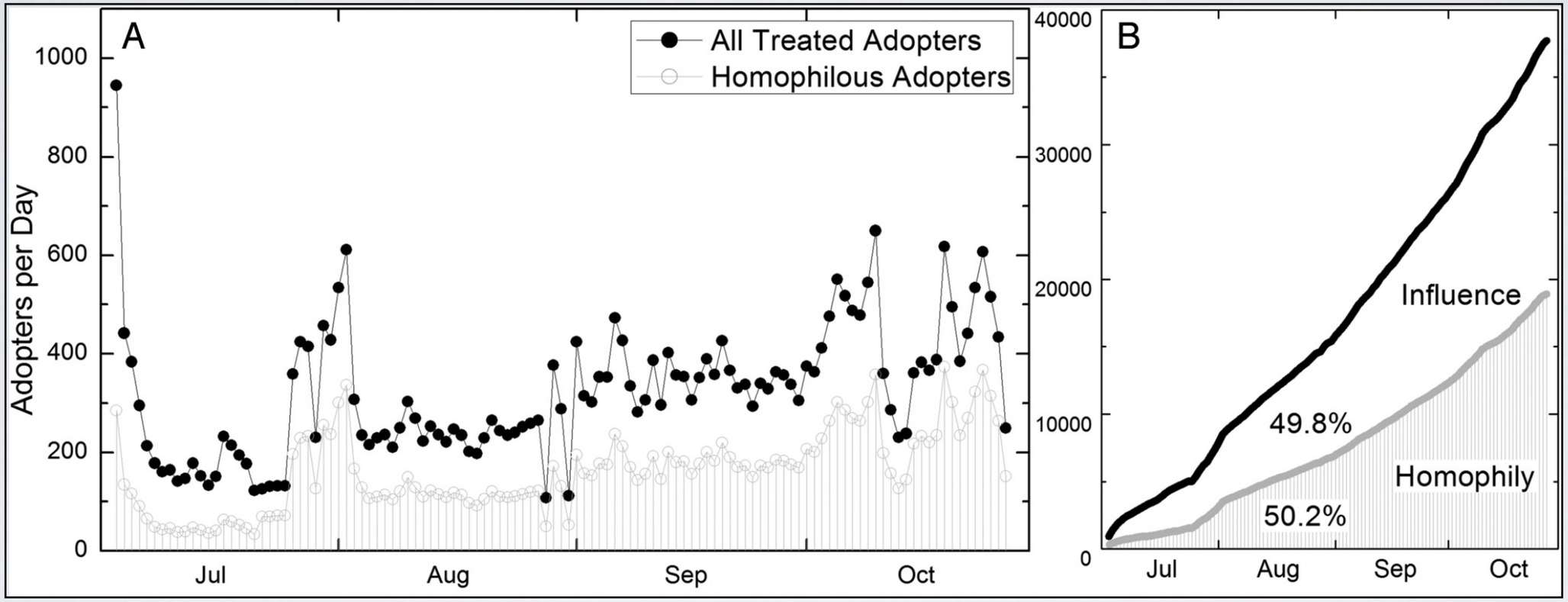

Is this social influence? ~50%

- 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”
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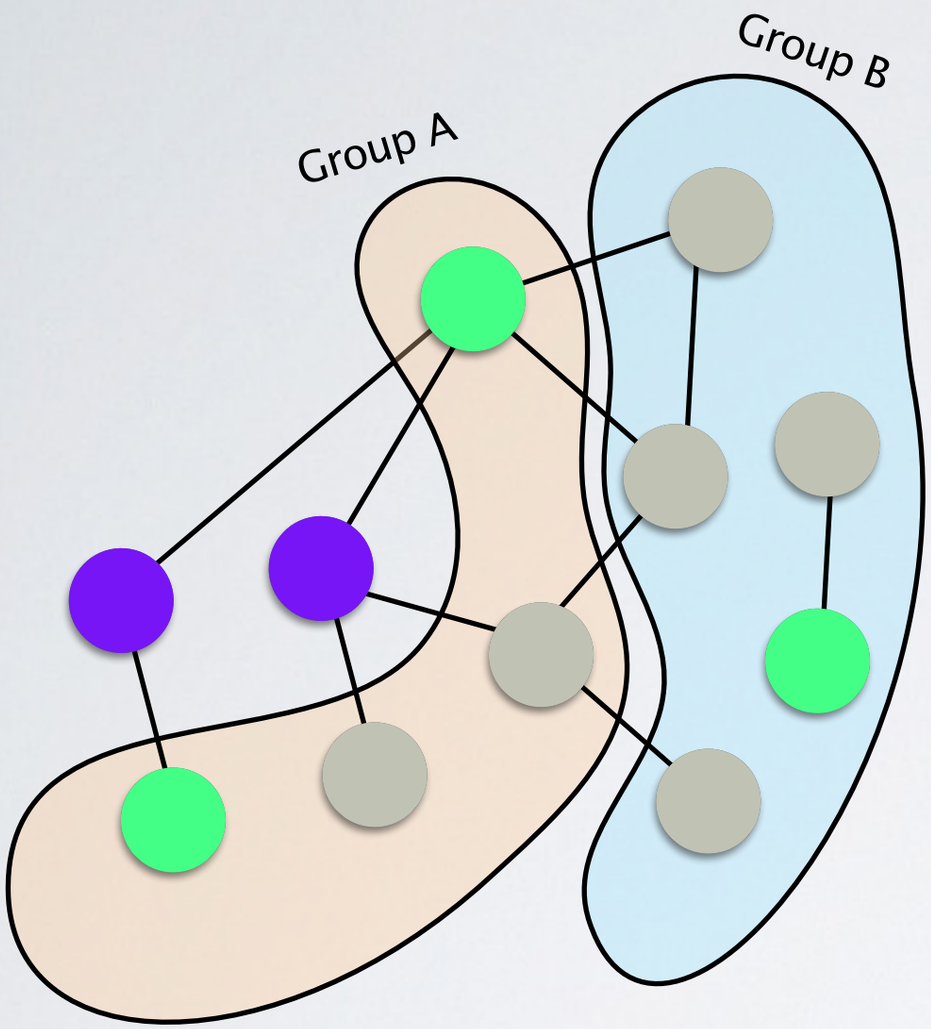
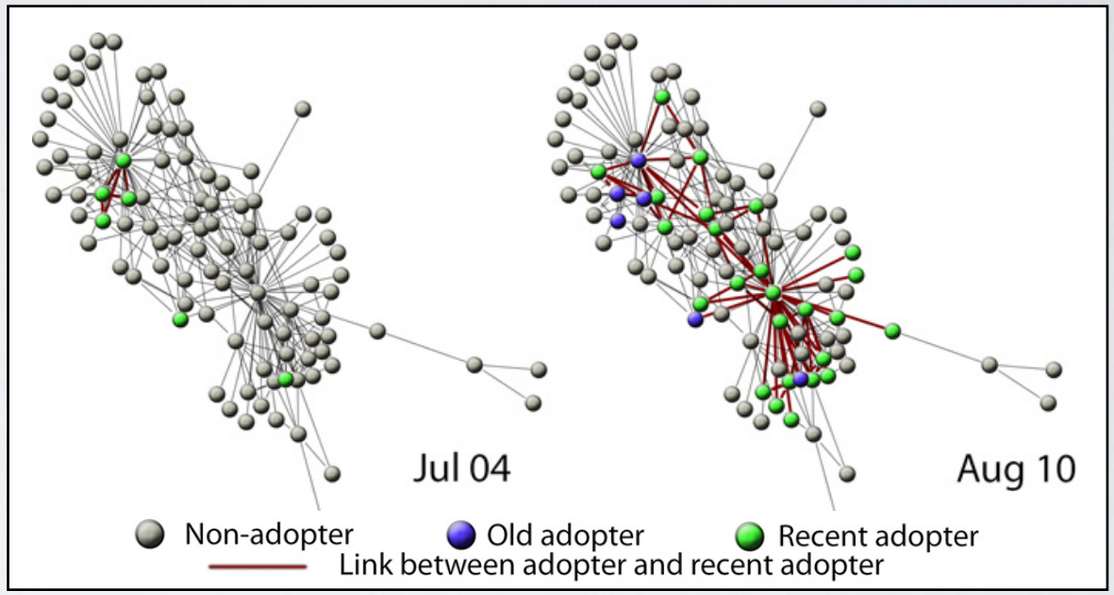
(Propensity score) matching





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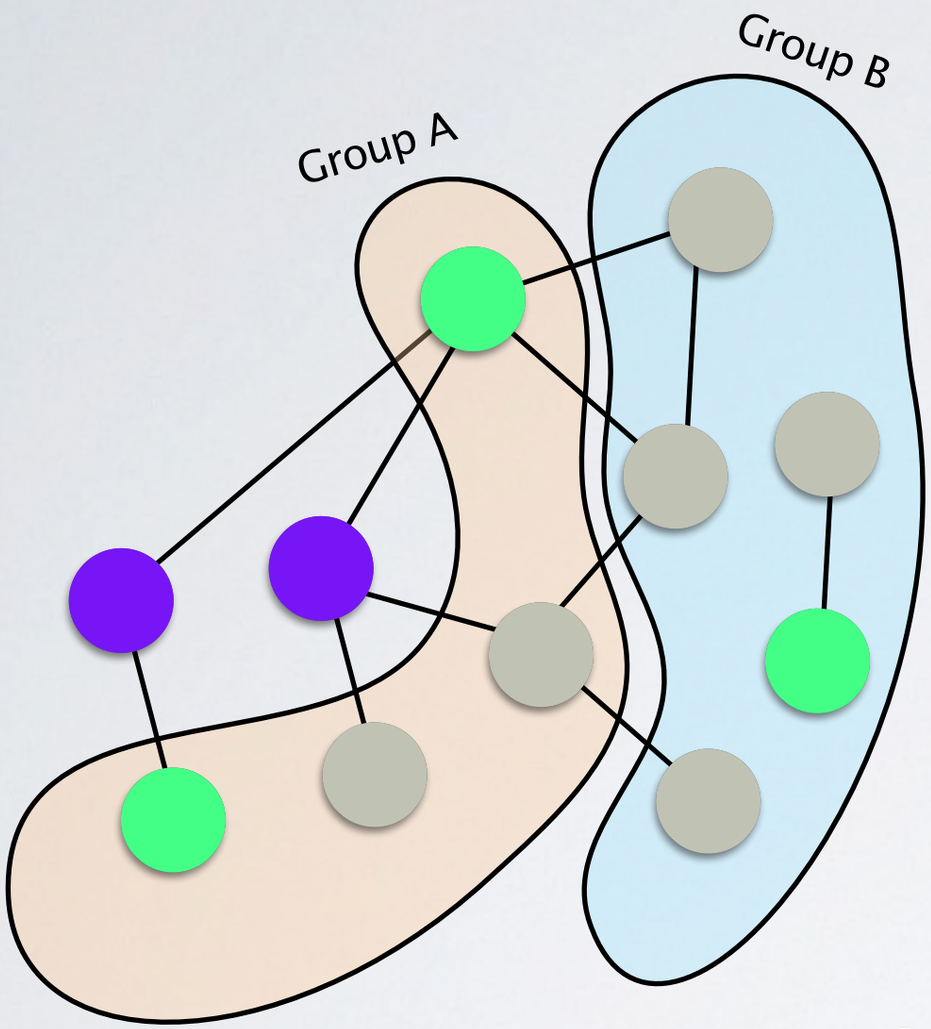
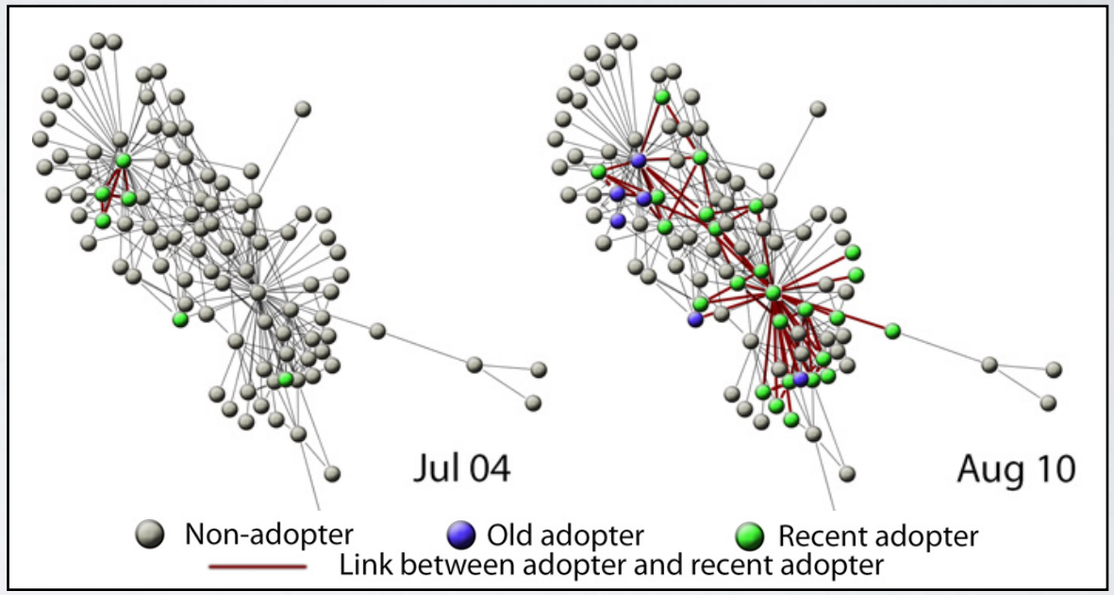




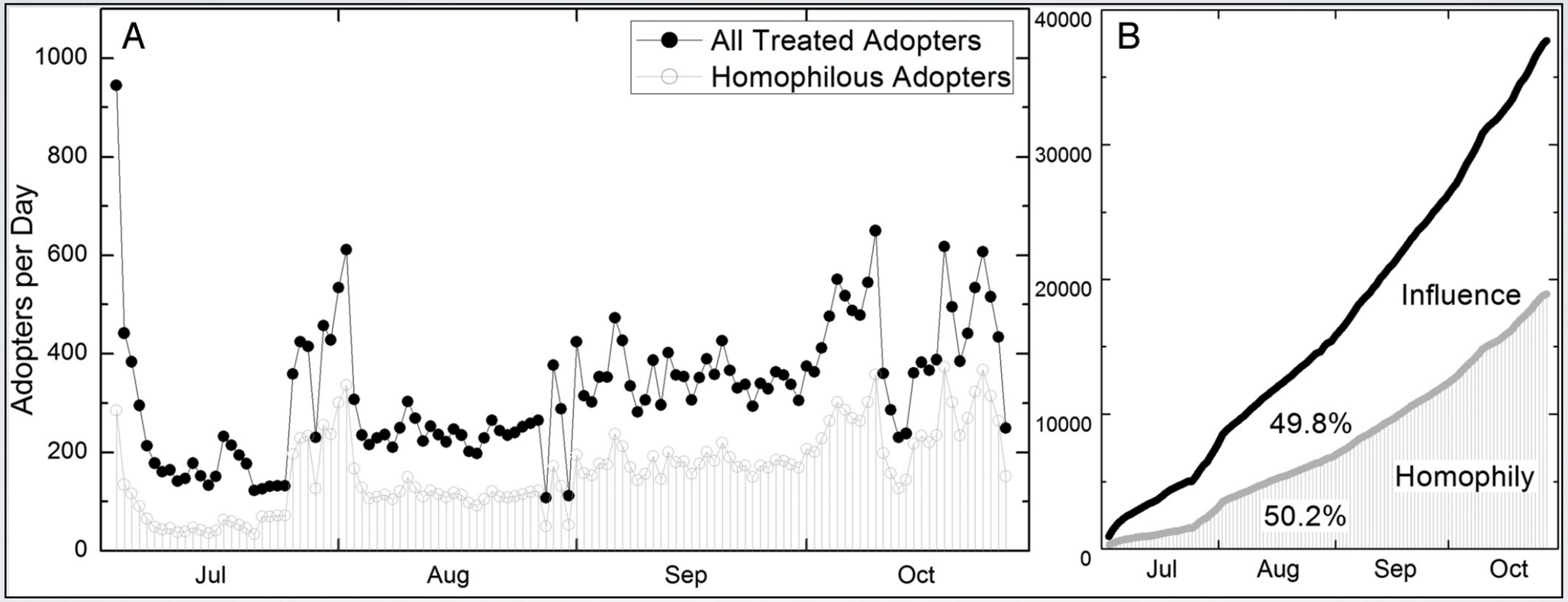
Match Group A (friends of early adopters) to Group B (rest of graph) so that the two groups have the same demographics.

Roughly: If group B has, e.g., too few young people, then “double count them”; plus 46 other traits.

- 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.

Propensity score matching

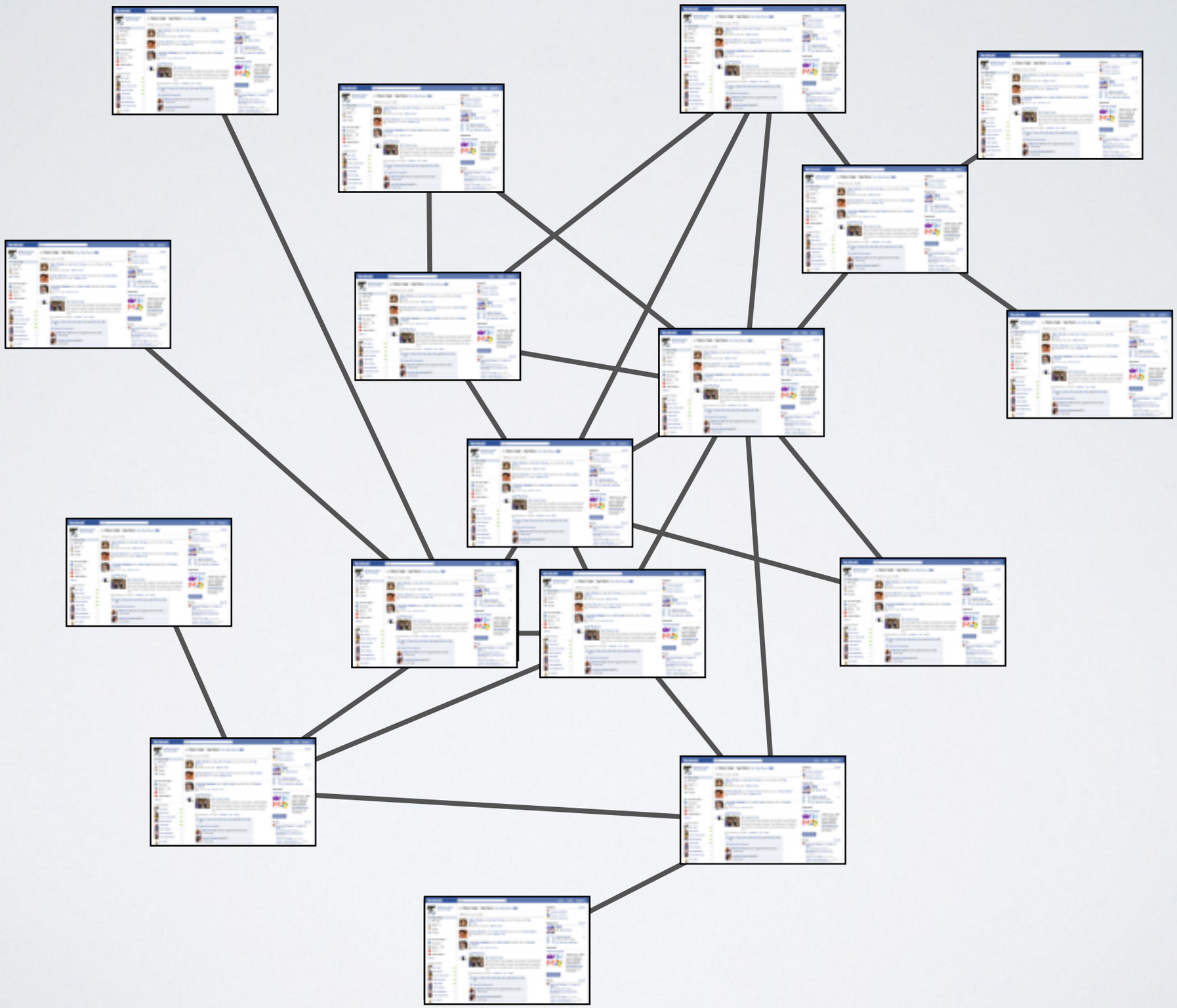
- (Aral et al. 2009): Yahoo! Go service, 2007.



~50% of users were adopting due to latent traits

- 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



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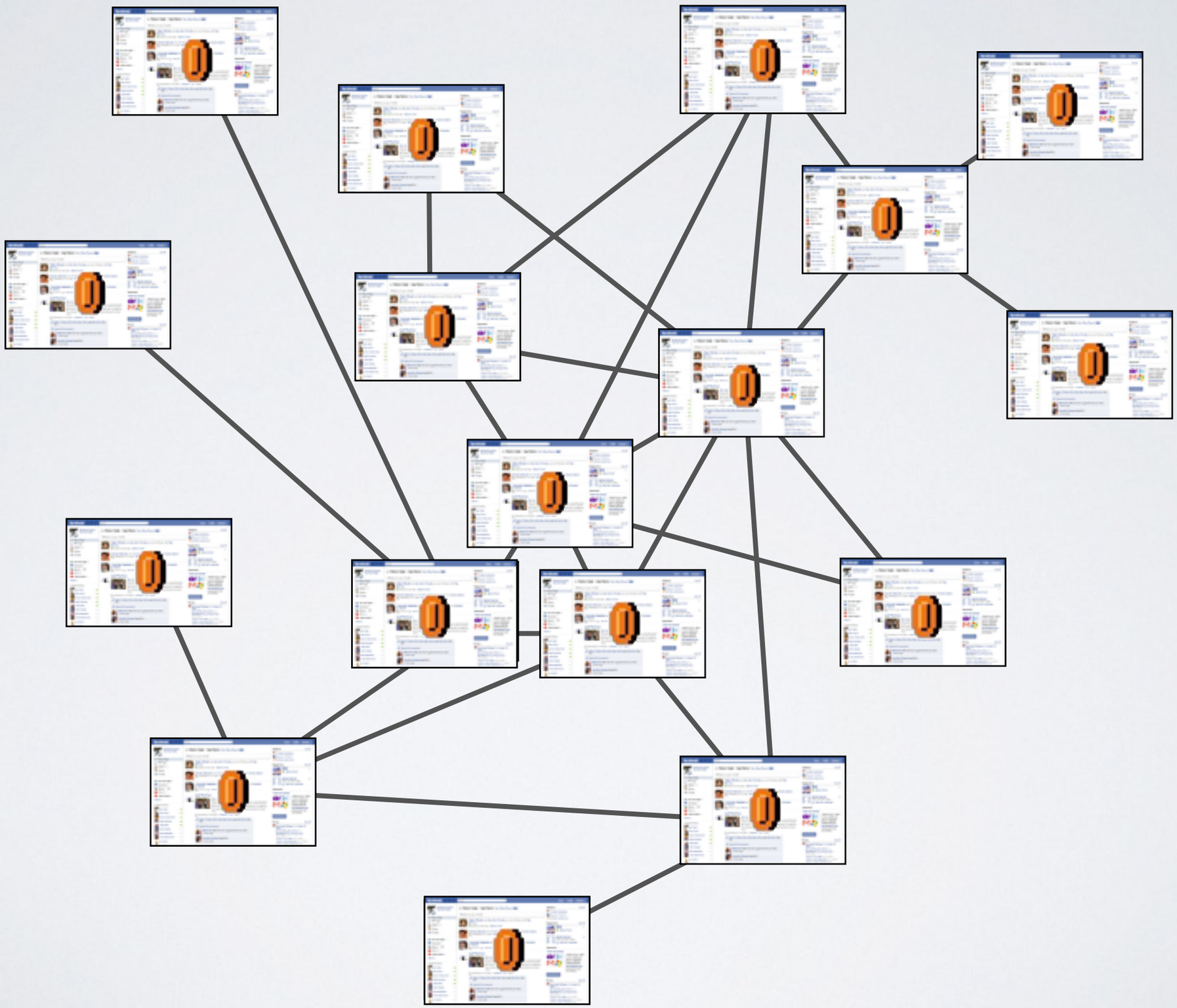

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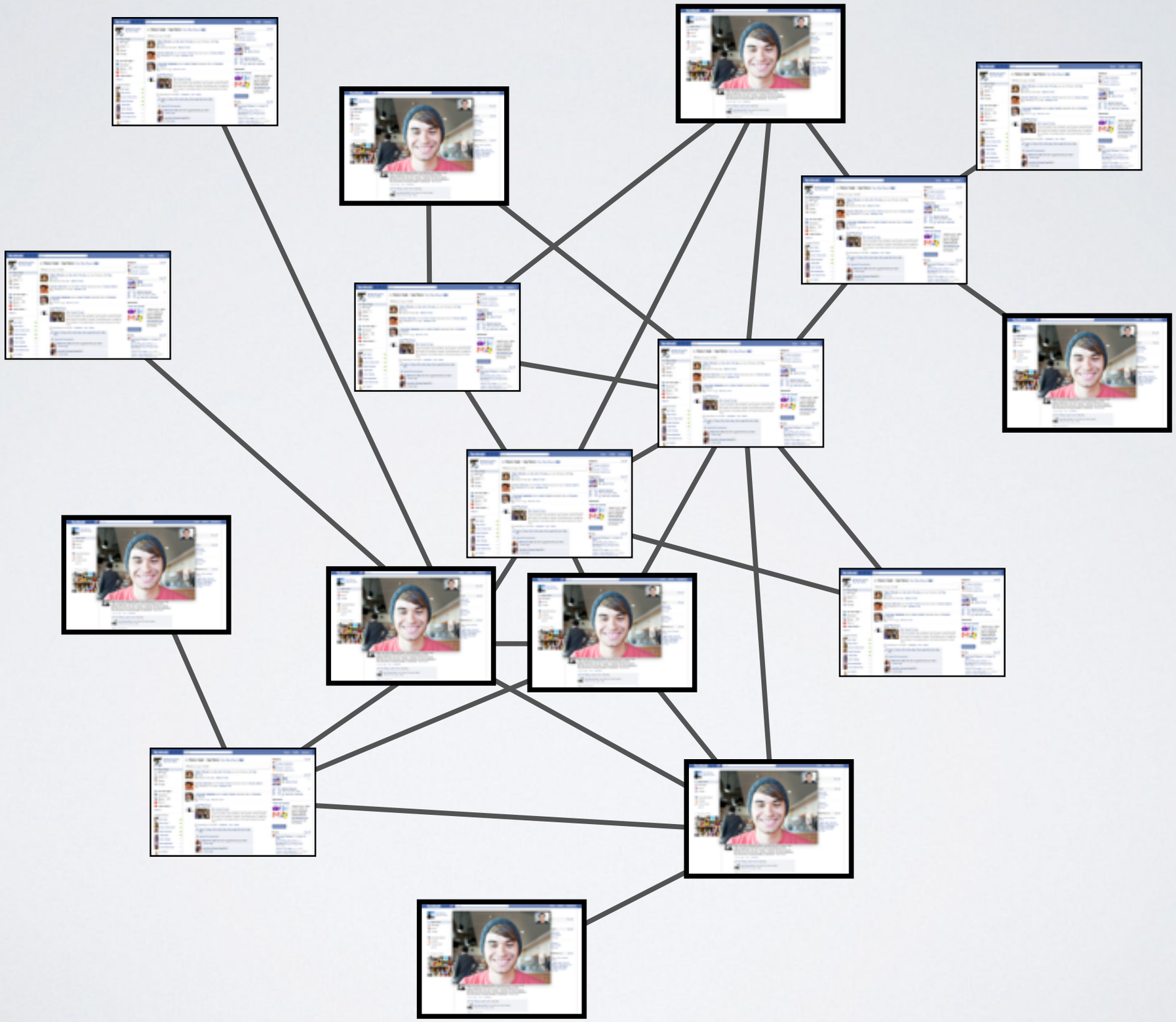
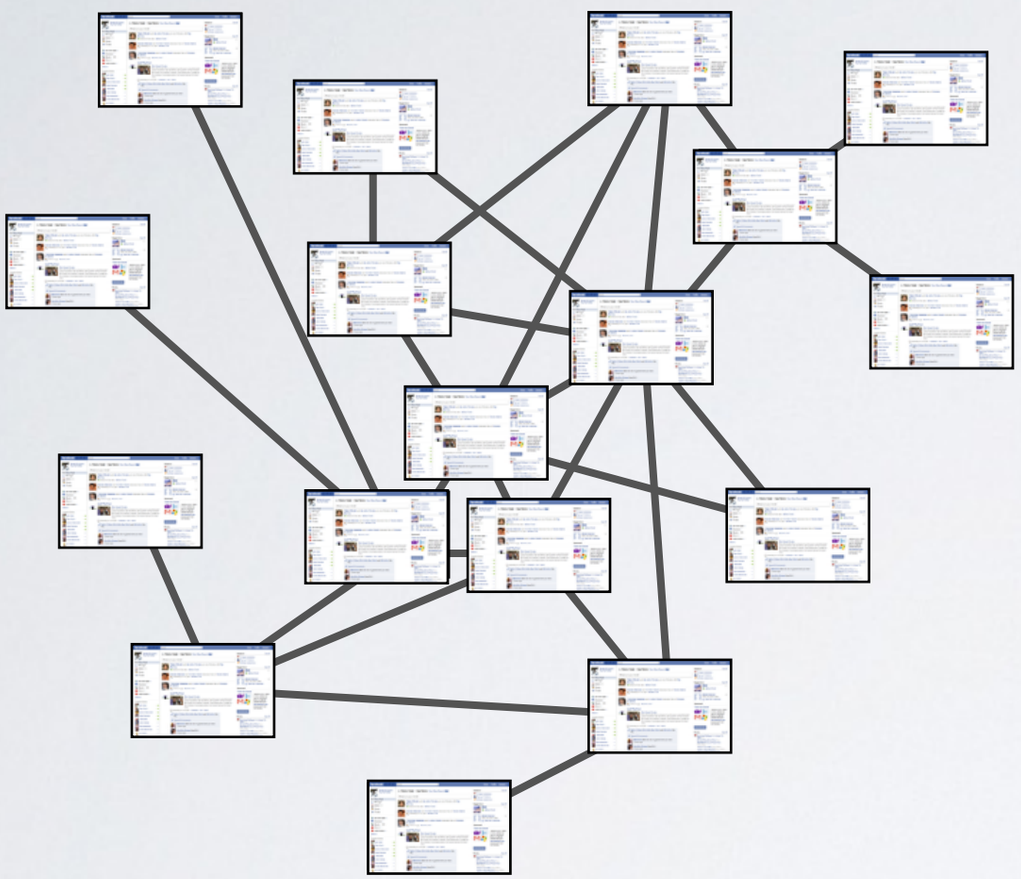
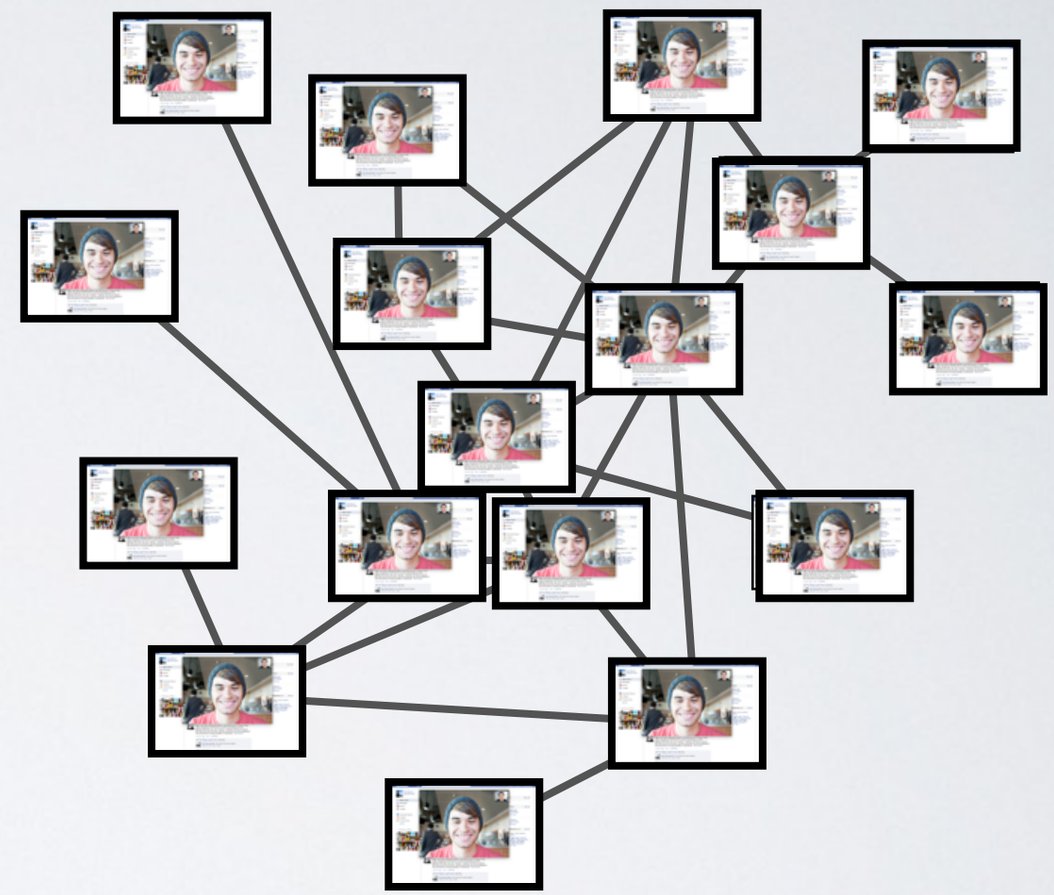


Causal inference & network effects

Universe A



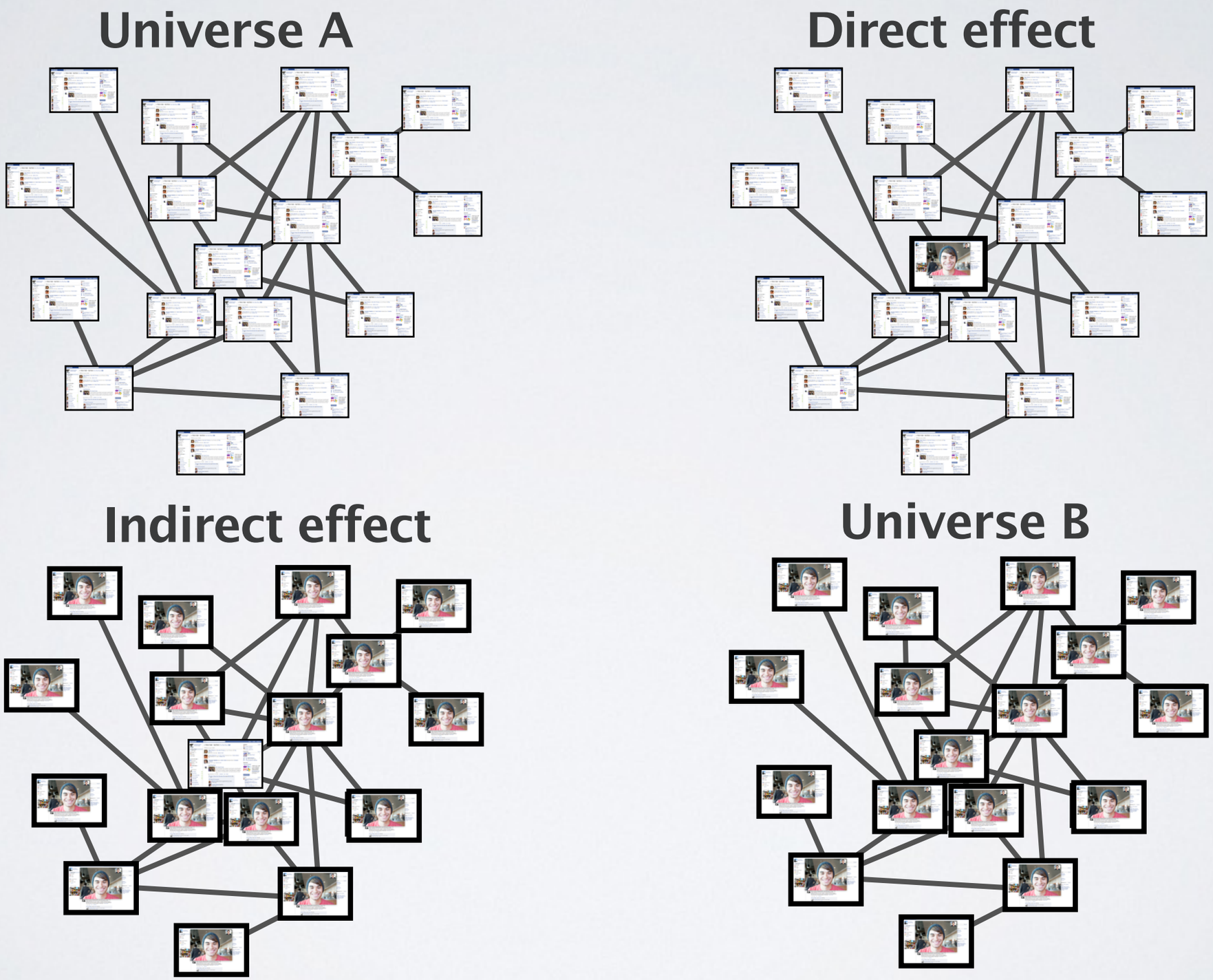
Universe B



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.

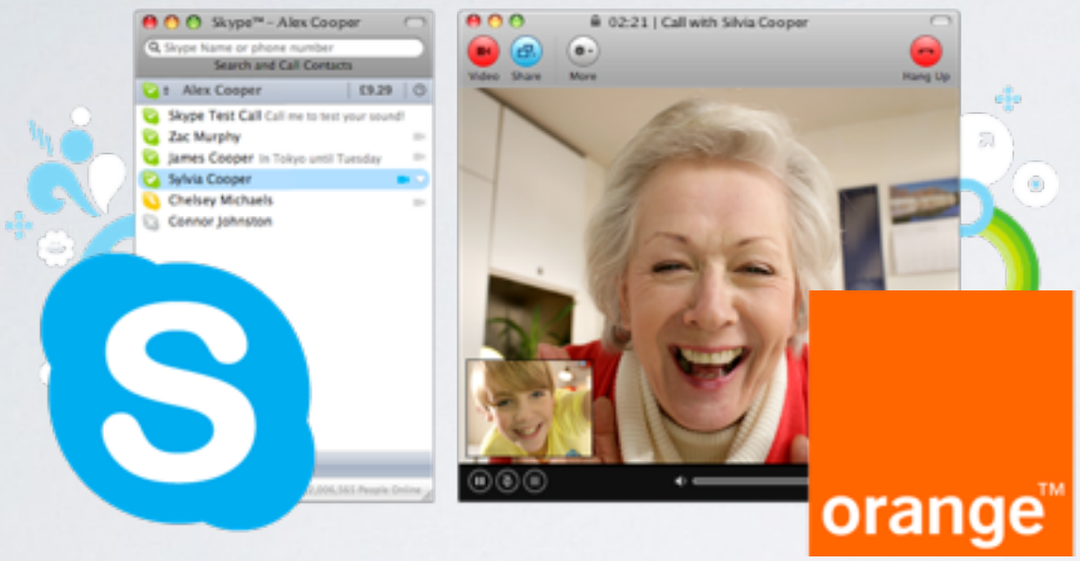
Direct vs. indirect effects



- 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.

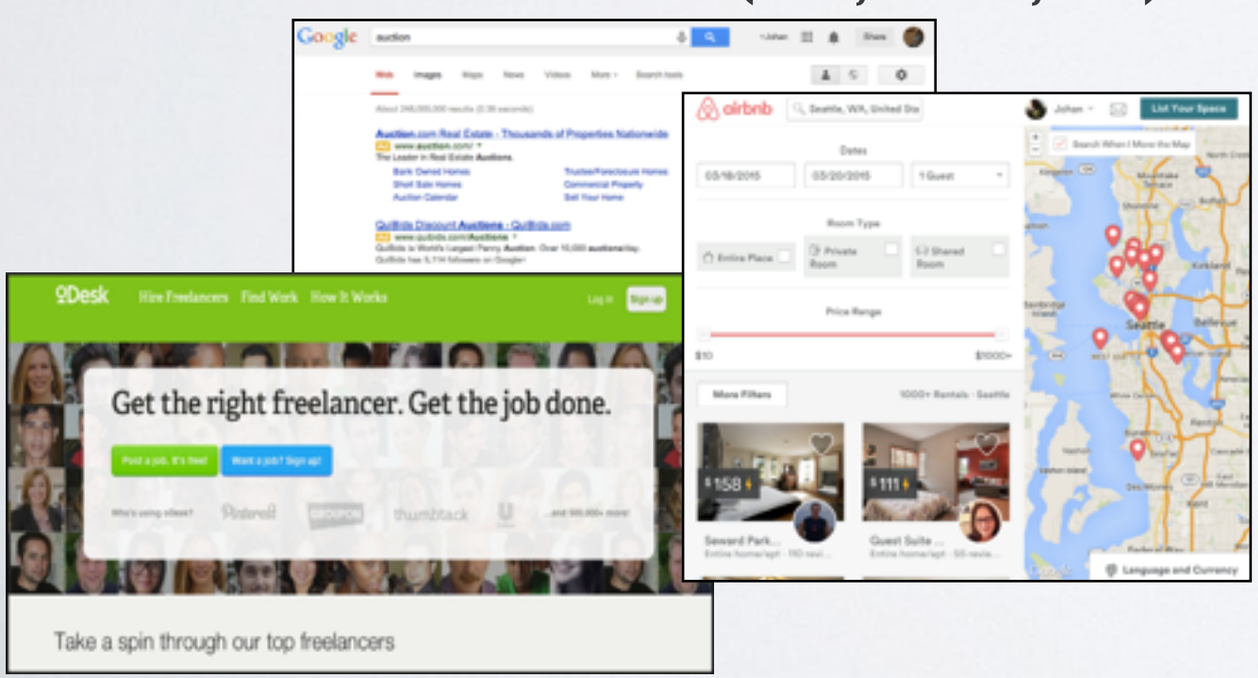
Experiments with interference

Chat/communication services

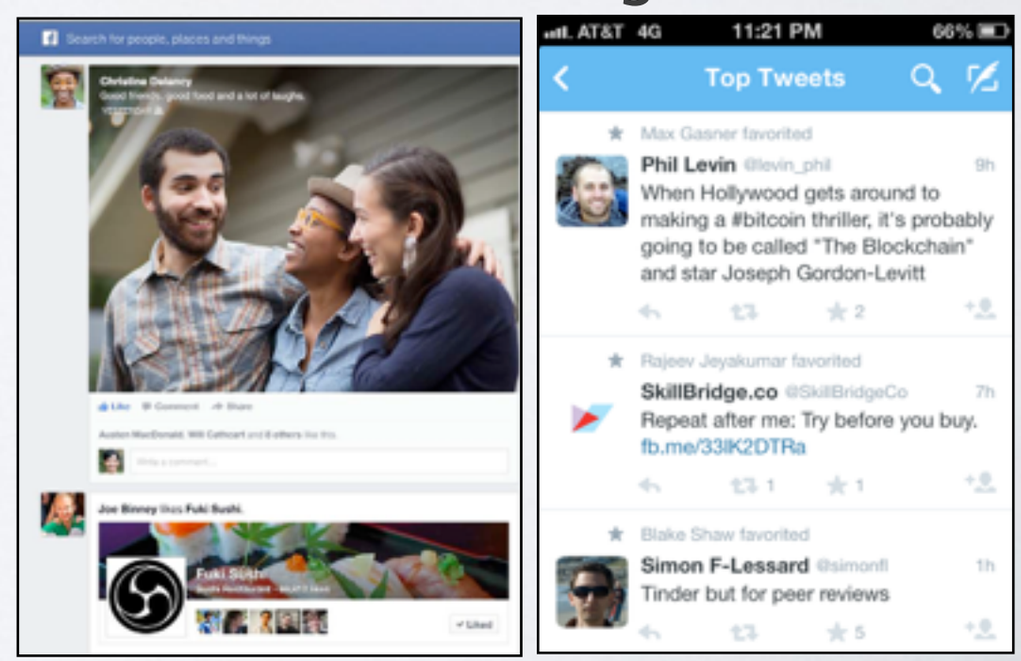


Social product design

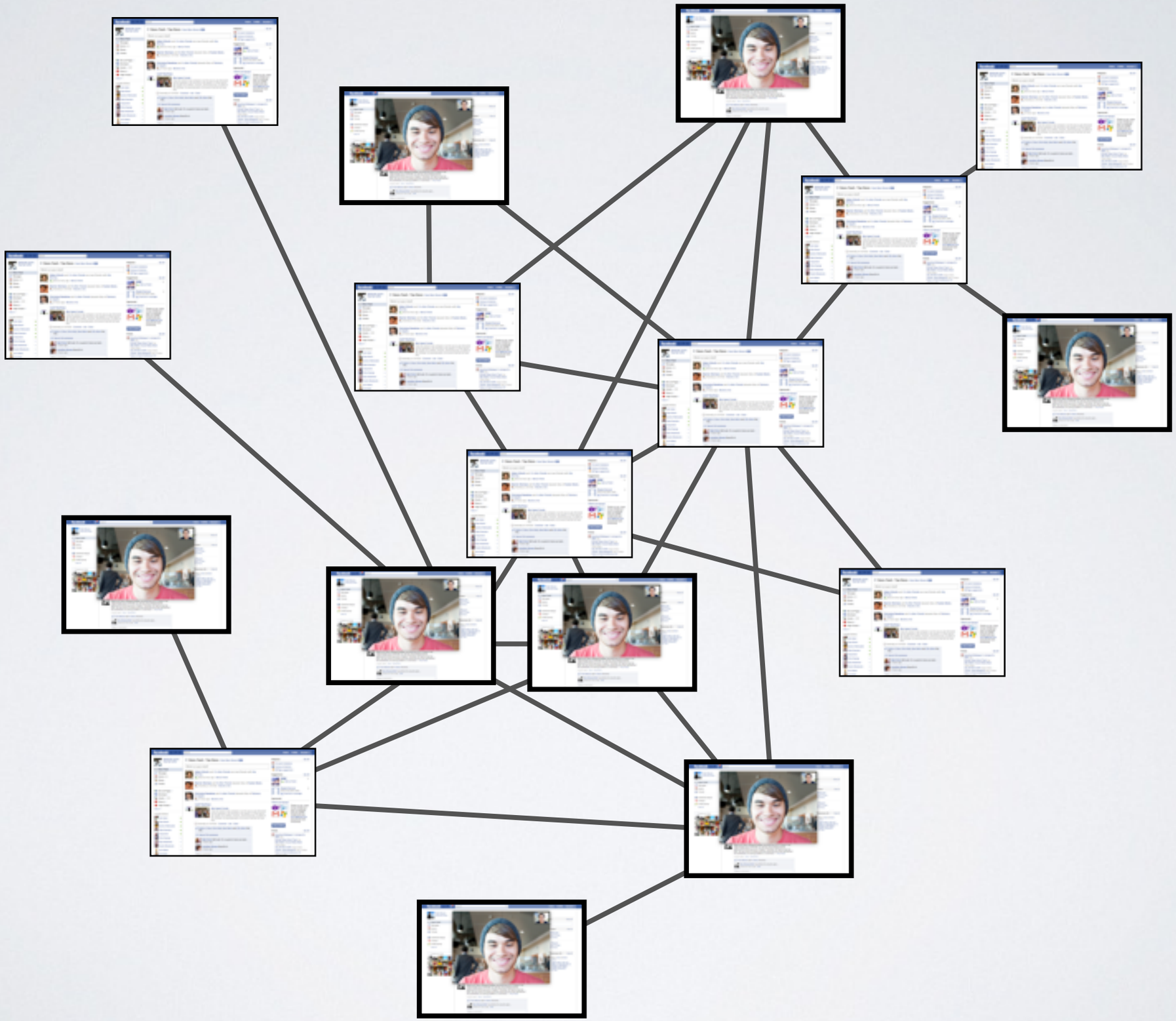
Market Mechanisms (ads, labor, etc)



Content ranking models



Design & Analysis



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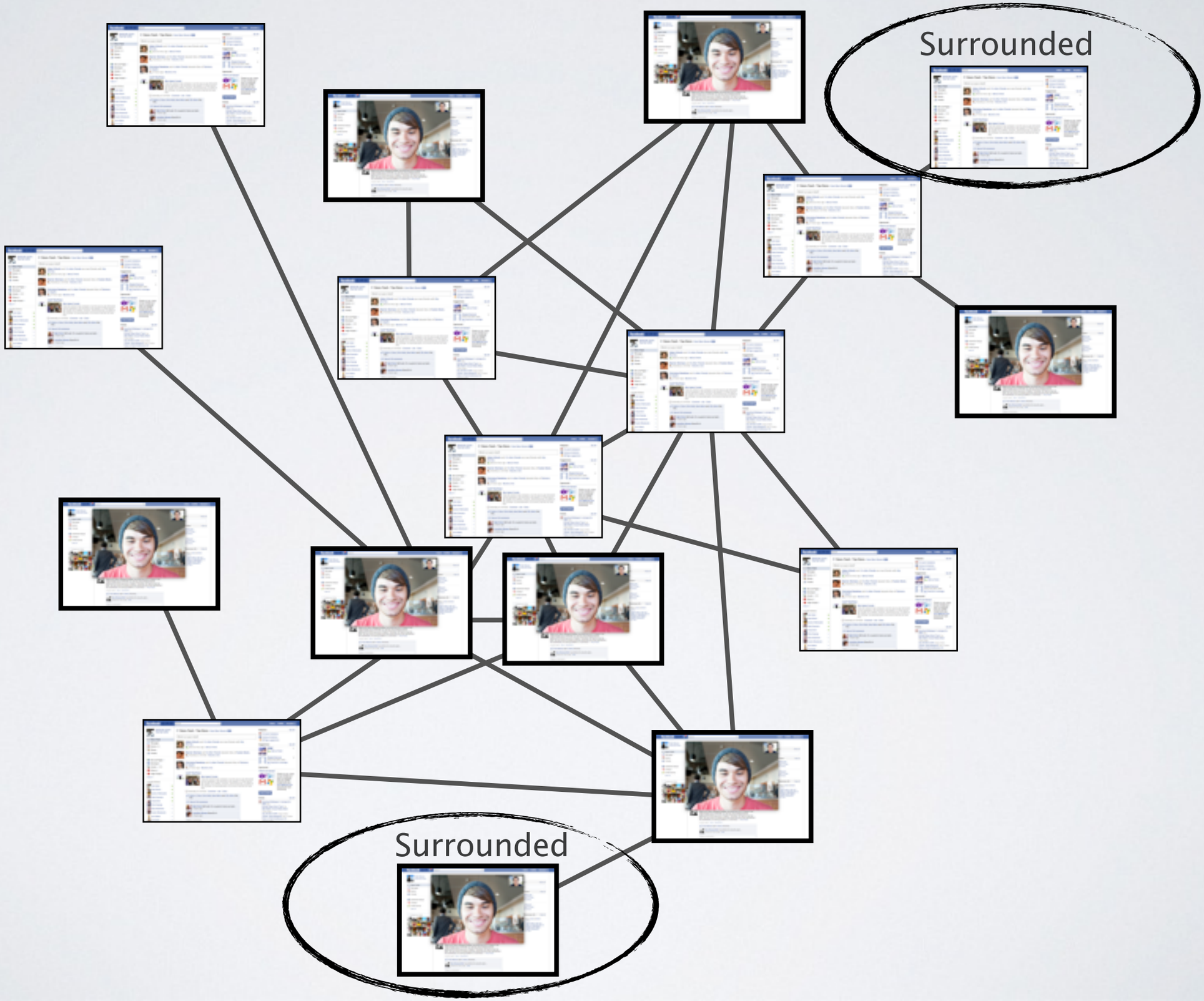

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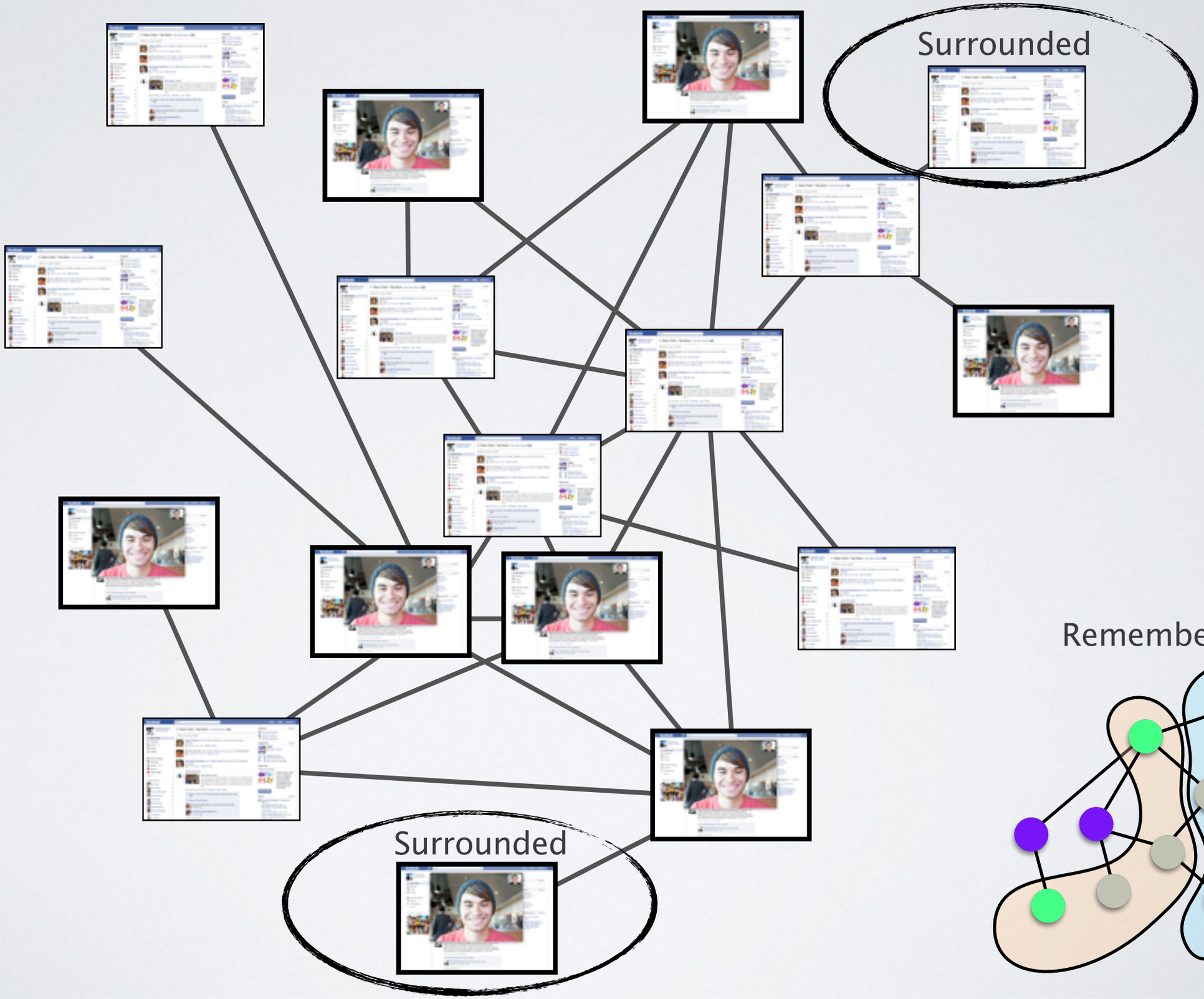

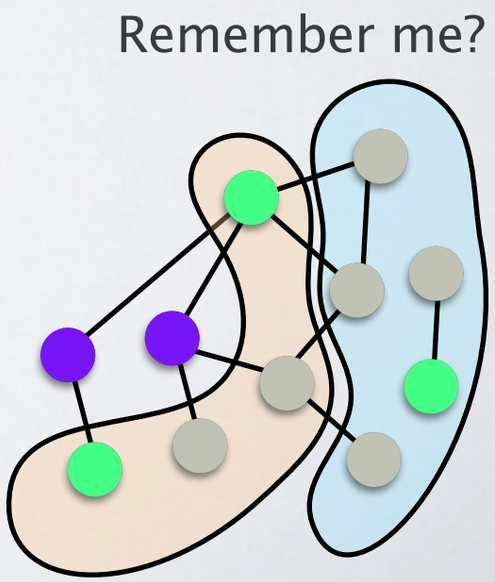

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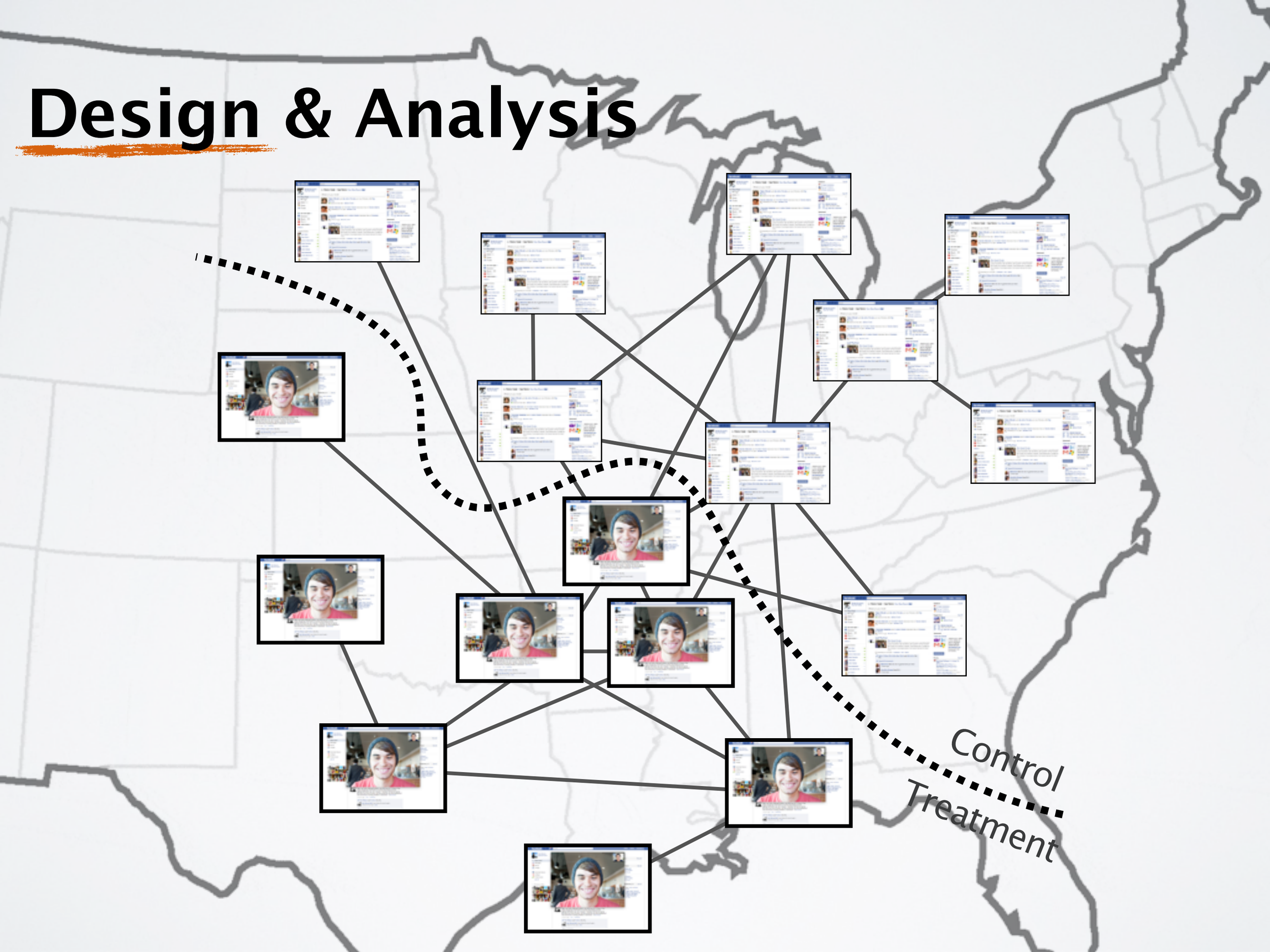

Average Treatment Effect

Treatment:

$z_i = 1$

$\rightarrow$ $Y_i(z_i = 1)$ = 60 min on site/day

$z_i = 0$

$\rightarrow$ $Y_i(z_i = 0)$ = 45 min on site/day

Response:

Average Treatment Effect:

$$\tau = \frac{1}{n}\sum_{i=1}^{n}(Y_i(z_i = 1) - Y_i(z_i = 0)).$$

Average Treatment Effect

Treatment:

$z_i = 1$

$z_i = 0$

Response:

→ $Y_i(z_i = 1)$ = 60 min on site/day

→ $Y_i(z_i = 0)$ = 45 min on site/day

Average Treatment Effect:

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- **A/B testing:**
  - IID randomization, inverse probability weighting

$$\hat{\tau}(Z) = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i(Z_i = 1)\frac{\mathbf{1}[Z_i = 1]}{\Pr(Z_i = 1)} - Y_i(Z_i = 0)\frac{\mathbf{1}[Z_i = 0]}{\Pr(Z_i = 0)}\right)$$

Average Treatment Effect

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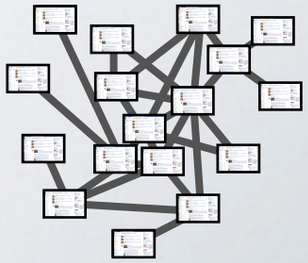
- **Introduce sets:** $\sigma_i^1 \subseteq \{0,1\}^n$, $\quad Y_i(Z \in \sigma_i^0) \approx Y_i(Z = \vec{0})$

  $\sigma_i^0 \subseteq \{0,1\}^n$, $\quad Y_i(Z \in \sigma_i^1) \approx Y_i(Z = \vec{1})$

$Z = \vec{1}$

$Z = \vec{0}$



Average Treatment Effect

Treatment: **Response:** **Average Treatment Effect:**

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$z_i = 0$

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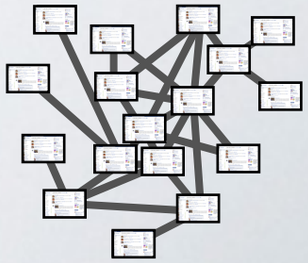
  $\sigma_i^0 \subseteq \{0,1\}^n$, $\quad Y_i(Z \in \sigma_i^1) \approx Y_i(Z = \vec{1})$

- **ATE with interference** (Aronow & Samii 2012, Manski 2013):

$$\hat{\tau}(Z) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{Y_i(Z)\mathbf{1}[Z \in \sigma_i^1]}{\Pr(Z \in \sigma_i^1)} - \frac{Y_i(Z)\mathbf{1}[Z \in \sigma_i^0]}{\Pr(Z \in \sigma_i^0)}\right)$$

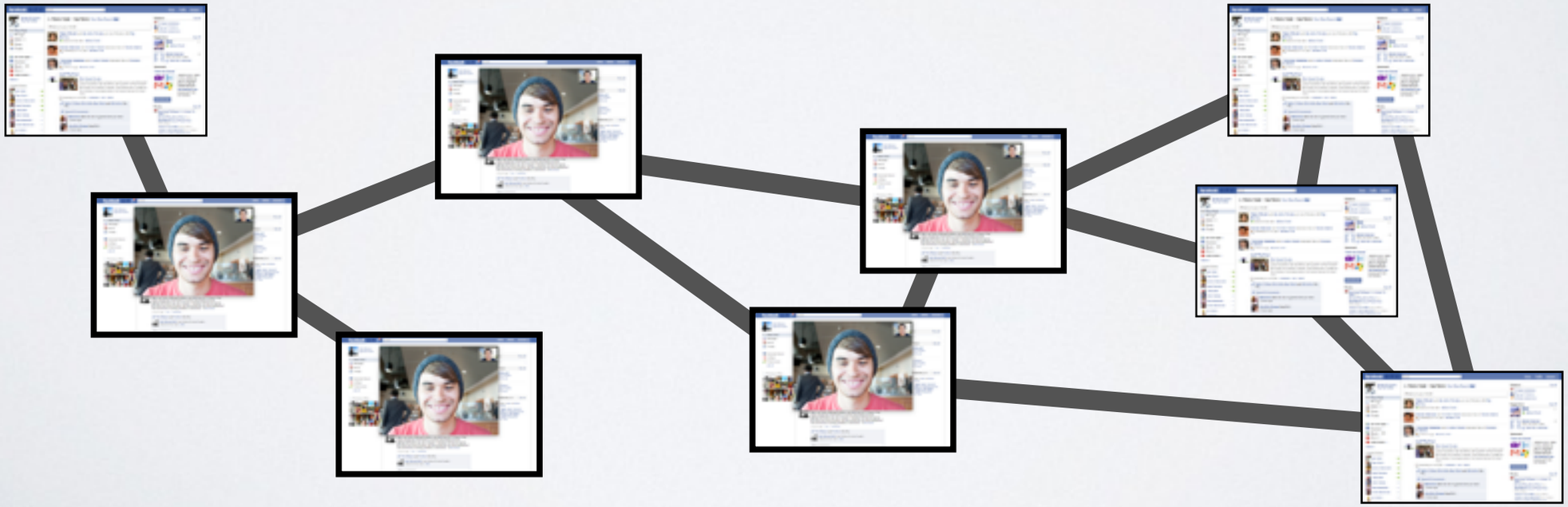
$Z = \vec{1}$

$Z = \vec{0}$

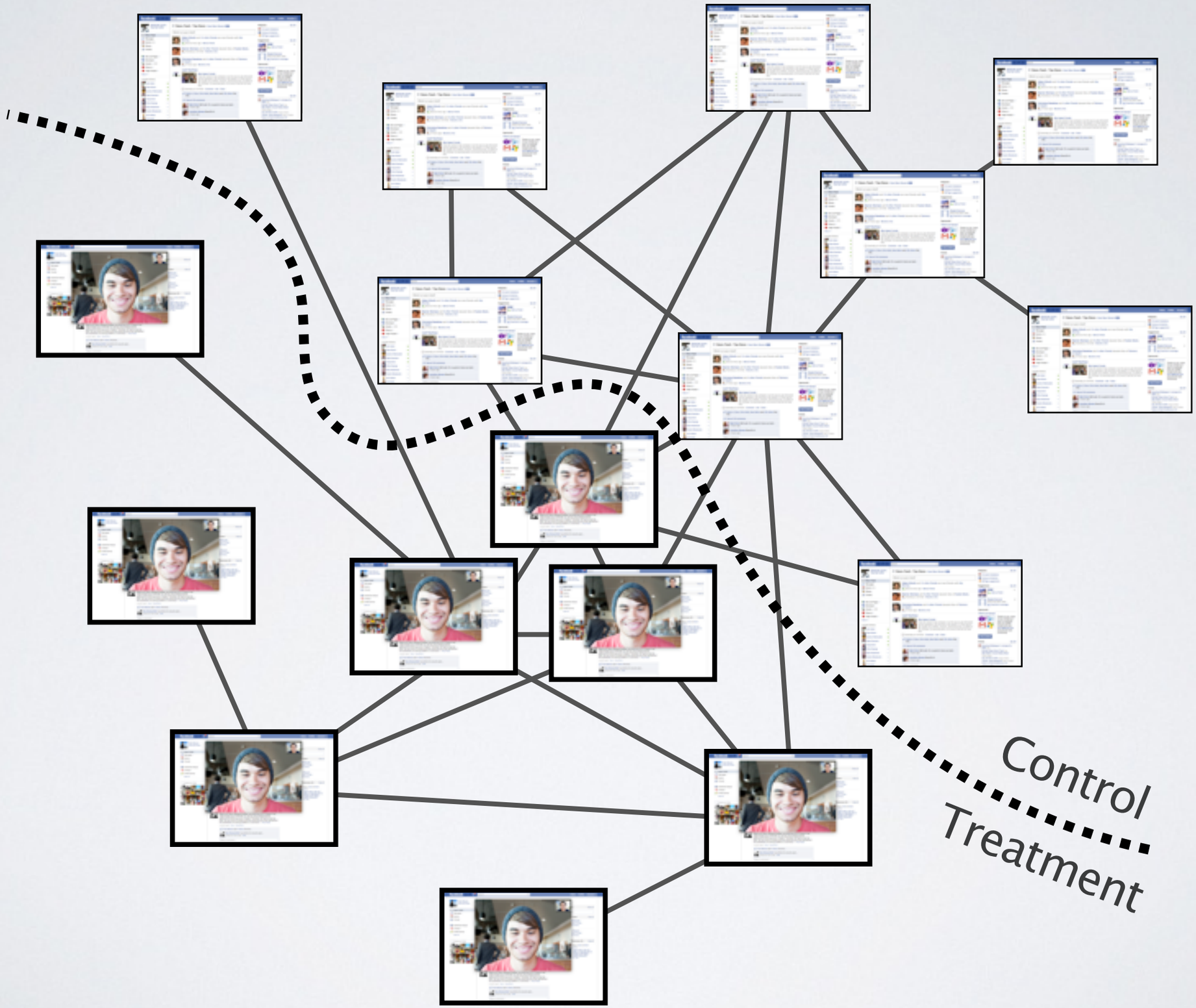


Analysis: “network exposure”


- Two **treatment conditions**: treatment/control.
- When are people **network exposed** to their treatment condition?
- **Neighborhood exposure** to treatment/control:
  - **Full neighborhood exposure**: you and all neighbors
  - **Fractional neighborhood exposure**: you and ≥q% neighbors
  - Many more notions are plausible



Design & Analysis



Design: how to assign?

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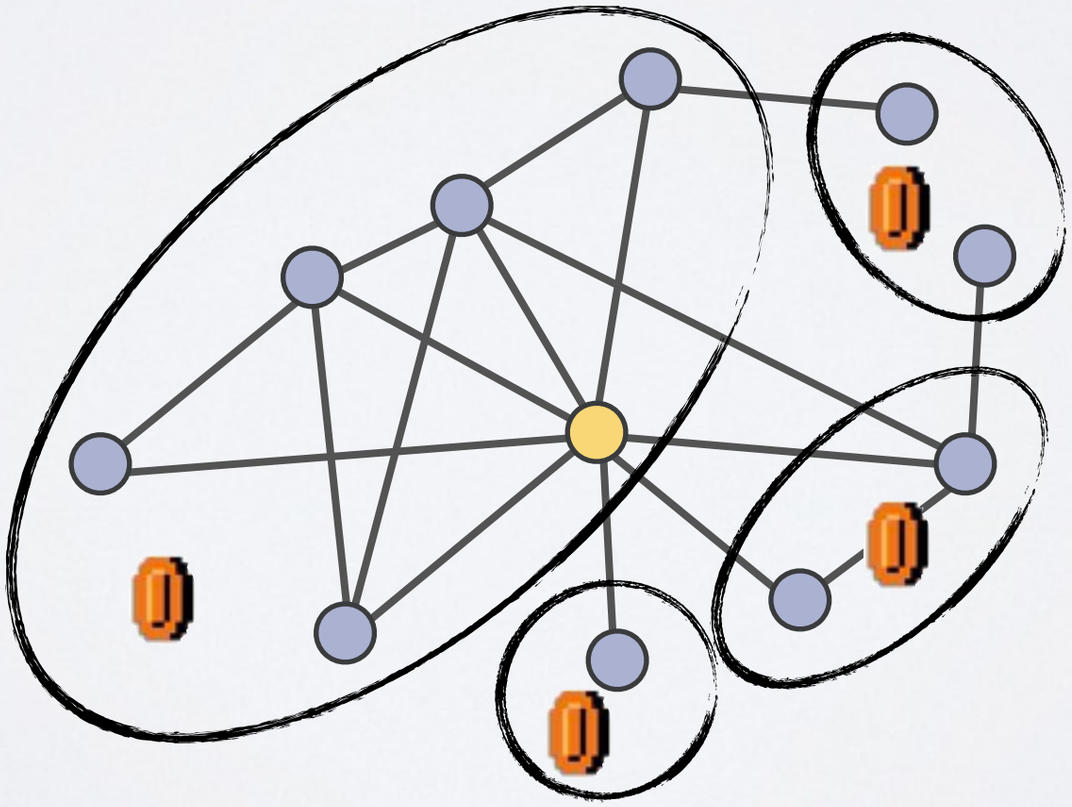
Design: graph cluster randomization

Assign vertices according to graph clusters:

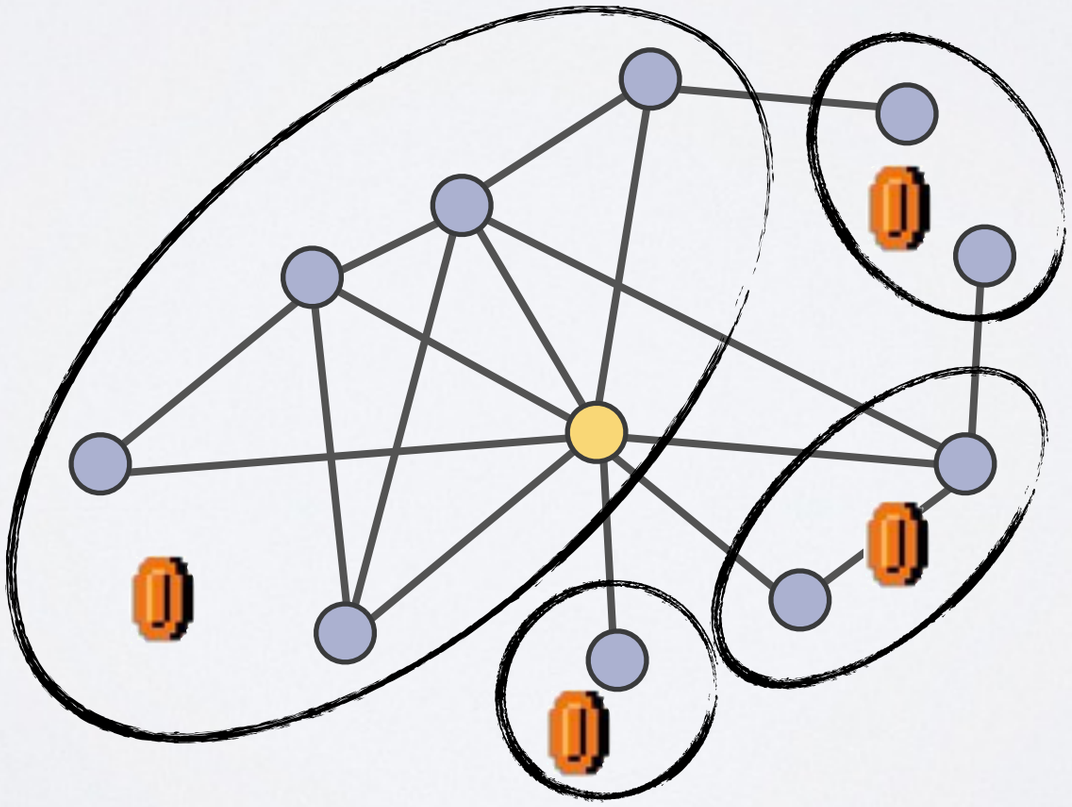
- Form clusters; assign each cluster to treatment with probability **p**
- Assign all vertices to their cluster's assignment



Design: graph cluster randomization

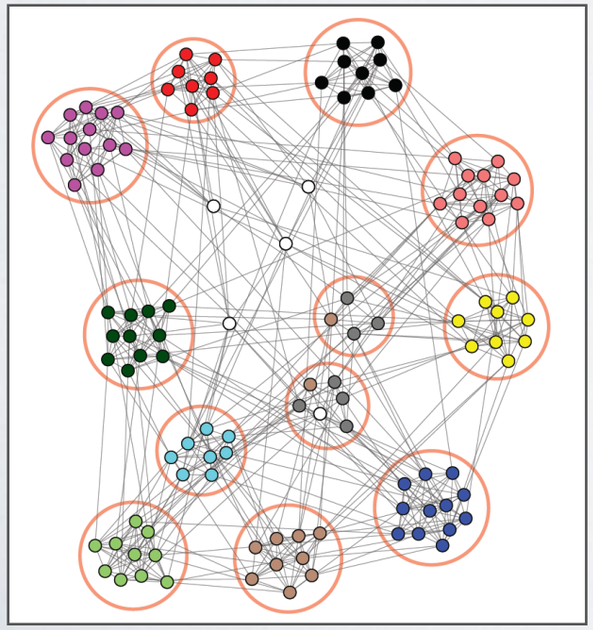
Assign vertices according to graph clusters:

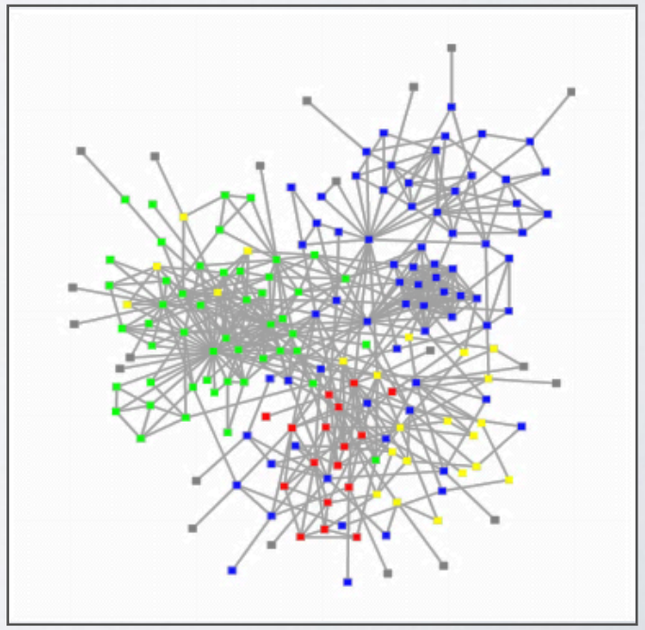
- Form clusters; assign each cluster to treatment with probability **p**
- Assign all vertices to their cluster's assignment
- Probability of full neighborhood exposure: $p^{(\#\text{ clusters connected to } i)}$
- Probability of fractional neighborhood exposure: **dynamic program**



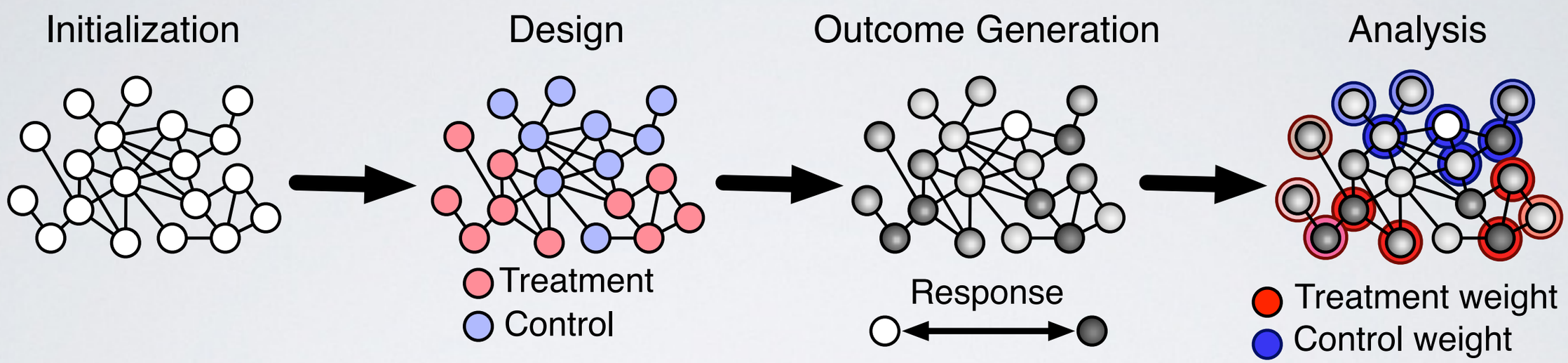
Algorithms for clustering

- Facebook: 1B+ vertices, 100B+ edges (countries still 100M+ vertices)
- Require highly scalable methods:
  - Label Propagation, Louvain method: [Zhu & Ghahramani 2002, Blondel et al. 2008]
  - Balanced Label Propagation: [Ugander & Backstrom 2013]
  - Streaming/Restreaming graph partitioning: [Stanton & Kliot 2012, Tsourakakis et al. 2012, Nishimura & Ugander 2013]
  - ϵ–net clustering: Variance bounds on graphs with restricted growth [Ugander et al. 2013, Karger & Ruhl 2002, Gupta, Krauthgamer & Lee 2003]





Network Experimentation



- **Initialization:** An empirical graph or graph model
- **Design:** Graph cluster randomization
- **Outcome generation:** Observe behavior (or observe model)
- **Analysis:** Discerning effective treatment

Clustered design & well-founded analysis can reduce bias and variance.

Summary

- Experiments to test social network theories continue to require innovative large-scale computation.
- Accelerating trend from **small data** to **big data** to **big experiments**.
- **Challenge:** influence maximization with realism.
- **Challenge:** improve theory for network data from disparate contexts (generalizability).
- **Challenge:** Propensity scores and null model statistics at scale and in difficult experiments.
- **Challenge:** applications of graph clustering/ community detection in experimental design