# ORIE 5355: People, Data, & Systems

## Lecture 13: Experimentation complications: peeking and interference

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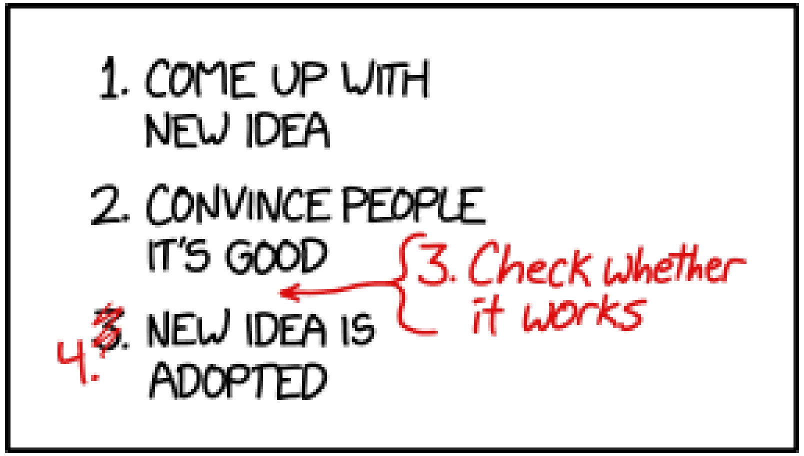
Course webpage: https://orie5355.github.io/Fall_2021/

# Announcements

- Today 11/1 guest lecture virtually: Hannah Li on marketplace experimentation
  - 6:15pm – 7:30 pm on Zoom
  - Will be recorded; required to watch it (will be on quiz)
  - Live attendance not required but is appreciated
- HW4 released; due next week
- Quiz 4 next week
- Project details released in next week
  - Project partner form on EdStem




THE INVENTION OF CLINICAL TRIALS

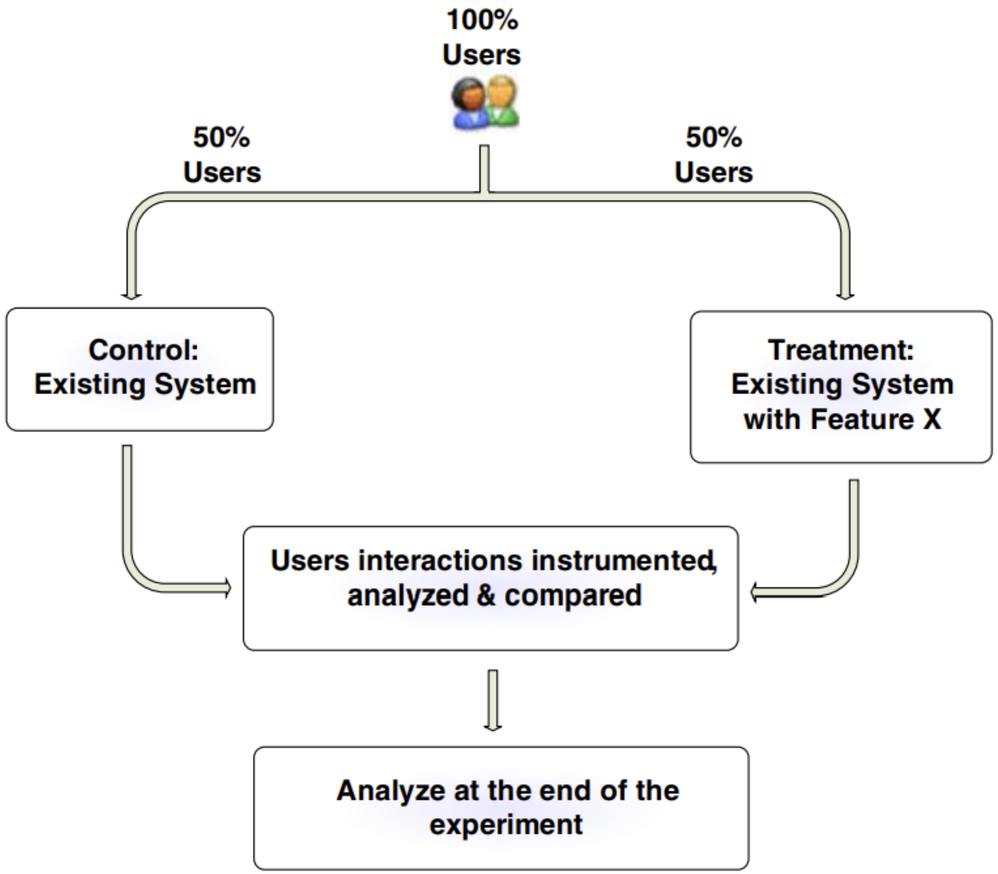
[xkcd: Clinical Trials]

# Peeking: a common mistake in running A/B tests in online marketplaces

# Basics of basic A/B testing

- Have an idea for a system change
- Give X% of your users the changed system, everyone else the old system

  Do this until you have N samples
- Decide the *metric* you care about
- Check if your system improved the metric
- Launch your product if good things happened

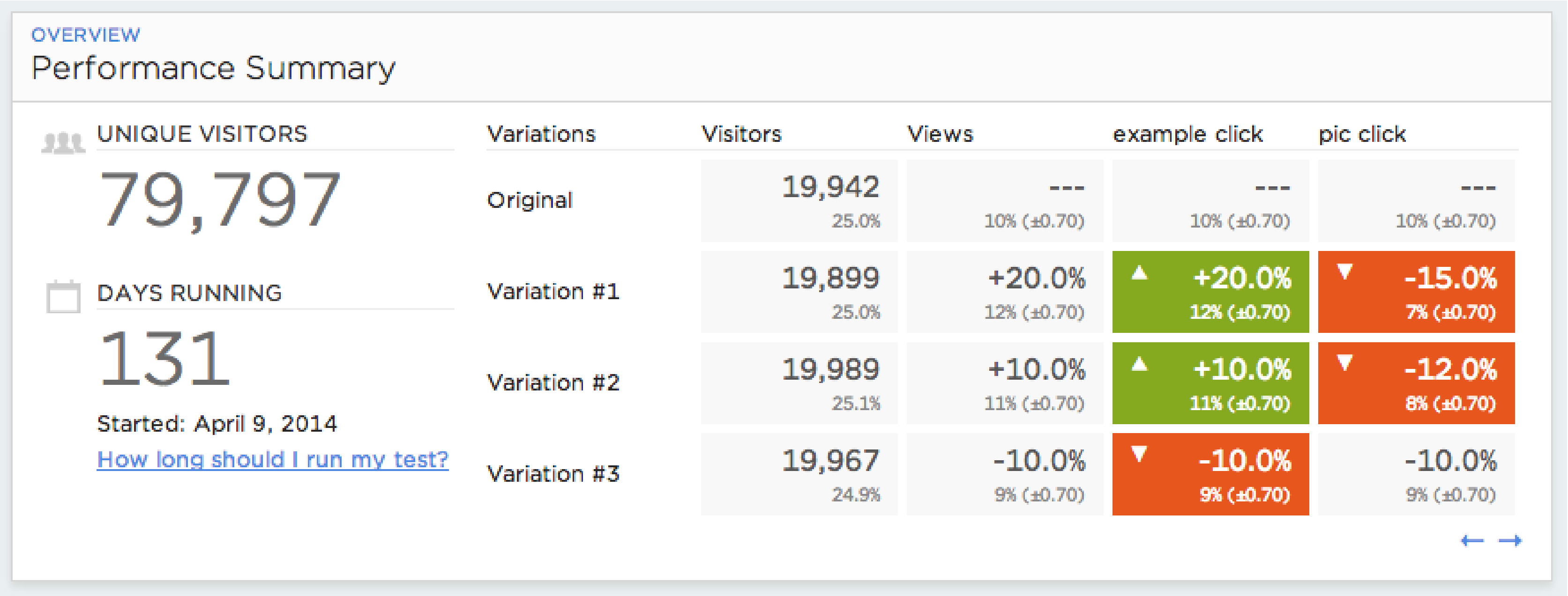



[Source: Controlled experiments on the web: survey and practical guide]

# Experiment Dashboards

In modern internet experiments, it's easy to see experimental results *while they are happening*

Sample results dashboard:




[Image credit: Ramesh Johari (Stanford; also Optimizely at time of presentation)]

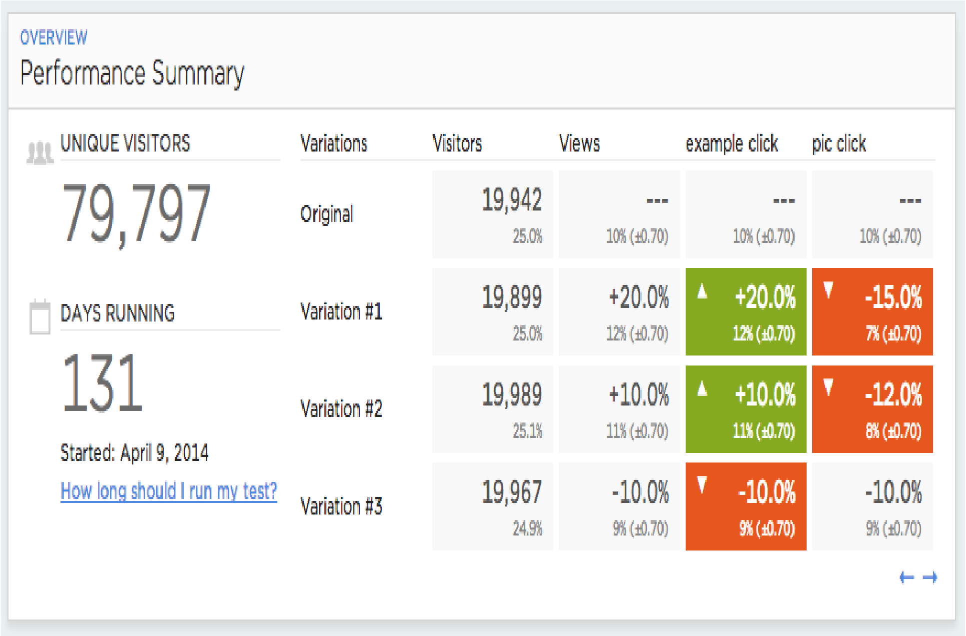
# Peeking

In modern online setting, the approach I described above is wasteful

So you continuously monitor (stare at) the results dashboard.

You rely on the dashboard to tell you when your results are significant.

- As soon as results are significant, you end the test and declare victory
- This is called adaptive sample size testing:
  - You adjust the test length in real-time, based on the data coming in.
  - If difference $Y_1 - Y_0$ is *huge*, end the experiment early




[Slide credit: Ramesh Johari (Stanford; also Optimizely at time of presentation)]

# Effect of peeking

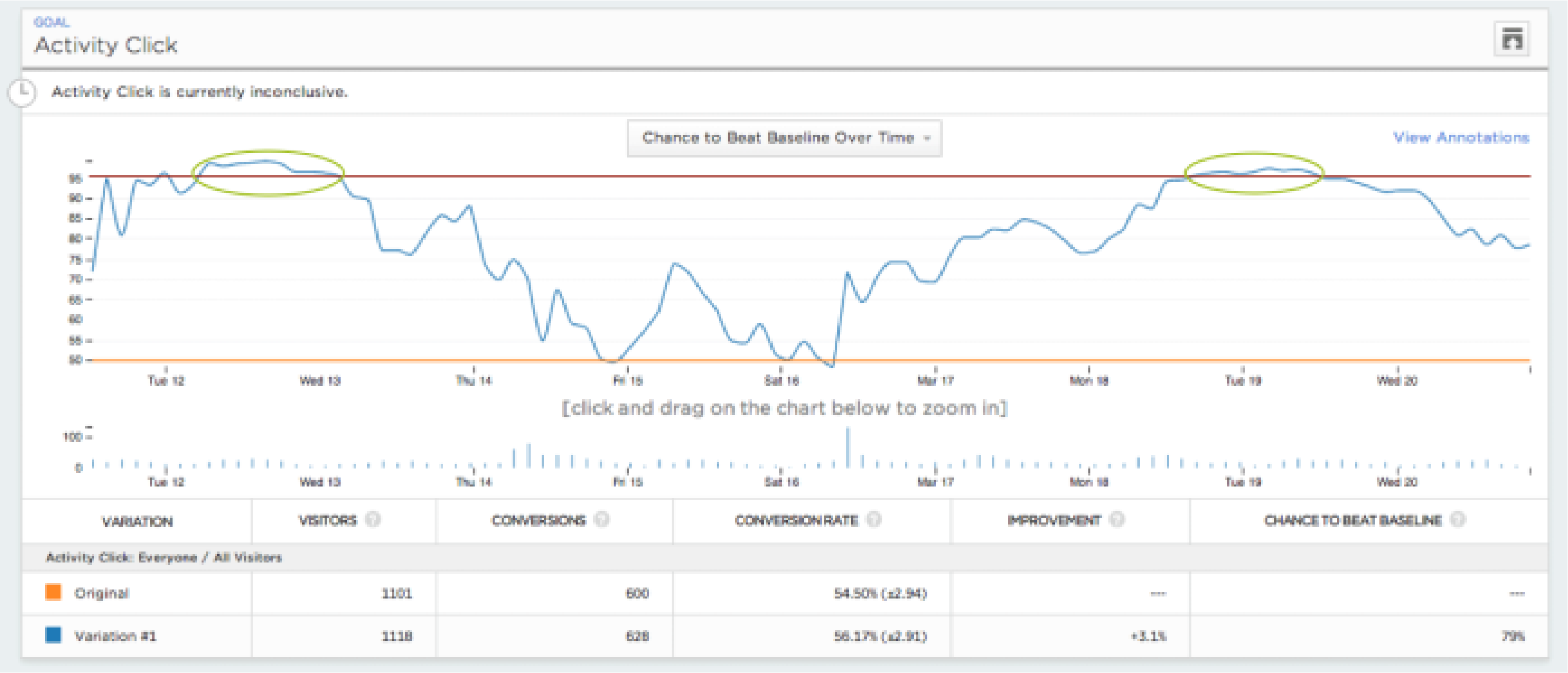
- Suppose 100 different individuals run A/A tests (same arm is treatment and control, so you know that $Y_1 - Y_0 = 0$)
- Each continuously monitors the dashboard, and waits for a significant result, i.e., p-value < 5% (up to a maximum of 10,000 visitors).
- *How many find a significant result and stop early?*

  Remember, $\alpha = 0.05$ means that if there is no true difference ($Y_1 - Y_0 = 0$), then 5% of the time you will falsely declare that $\hat{Y}_1 - \hat{Y}_0 \neq 0$ in a statistically significant way (false positive)
- Answer: **Over HALF!** find a significant result if they peek
- In A/B testing, "peeking" can dramatically inflate false positives.

[Slide credit: Ramesh Johari (Stanford; also Optimizely at time of presentation)]

# What went wrong?

A sample run of an *A/A* test (graph is of p-values over time)




If you wait long enough, there is a high chance of an eventually inconclusive result looking “significant” along the way!

[Slide credit: Ramesh Johari (Stanford; also Optimizely at time of presentation)]

# Peeking: what to do about it

You have two options

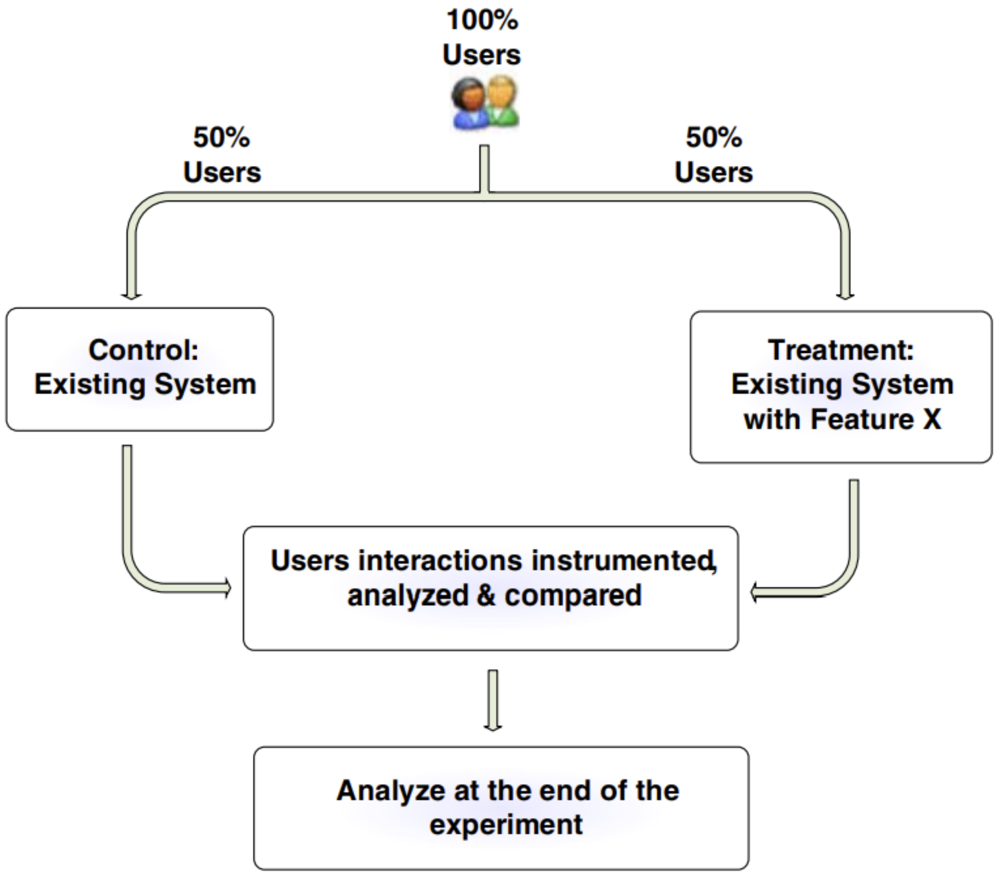
- Don't peek: set a sample size $N$ before the experiment starts, and don't end early no matter how large the effect is
  - Easy to do the statistics; no danger of inflating false positives
  - Could be **wasteful**: what if the effect is clearly huge?

    Even medical trials have a procedure to end early if a drug is clearly fantastic
- Peek, but do **fancy statistics** to make sure your p-values are valid
  - This is the approach Optimizely implemented on their dashboards
  - If you're at a big company with an established experimental culture, they (hopefully) have a dashboard that does this

# Interference in experimentation

# Basics of basic A/B testing

- Have an idea for a system change
- Give X% of your users the changed system, everyone else the old system
  Independently assign each user to treatment or control
- Decide the *metric* you care about
- Check if your system improved the metric
- Launch your product if good things happened




[Source: Controlled experiments on the web: survey and practical guide]

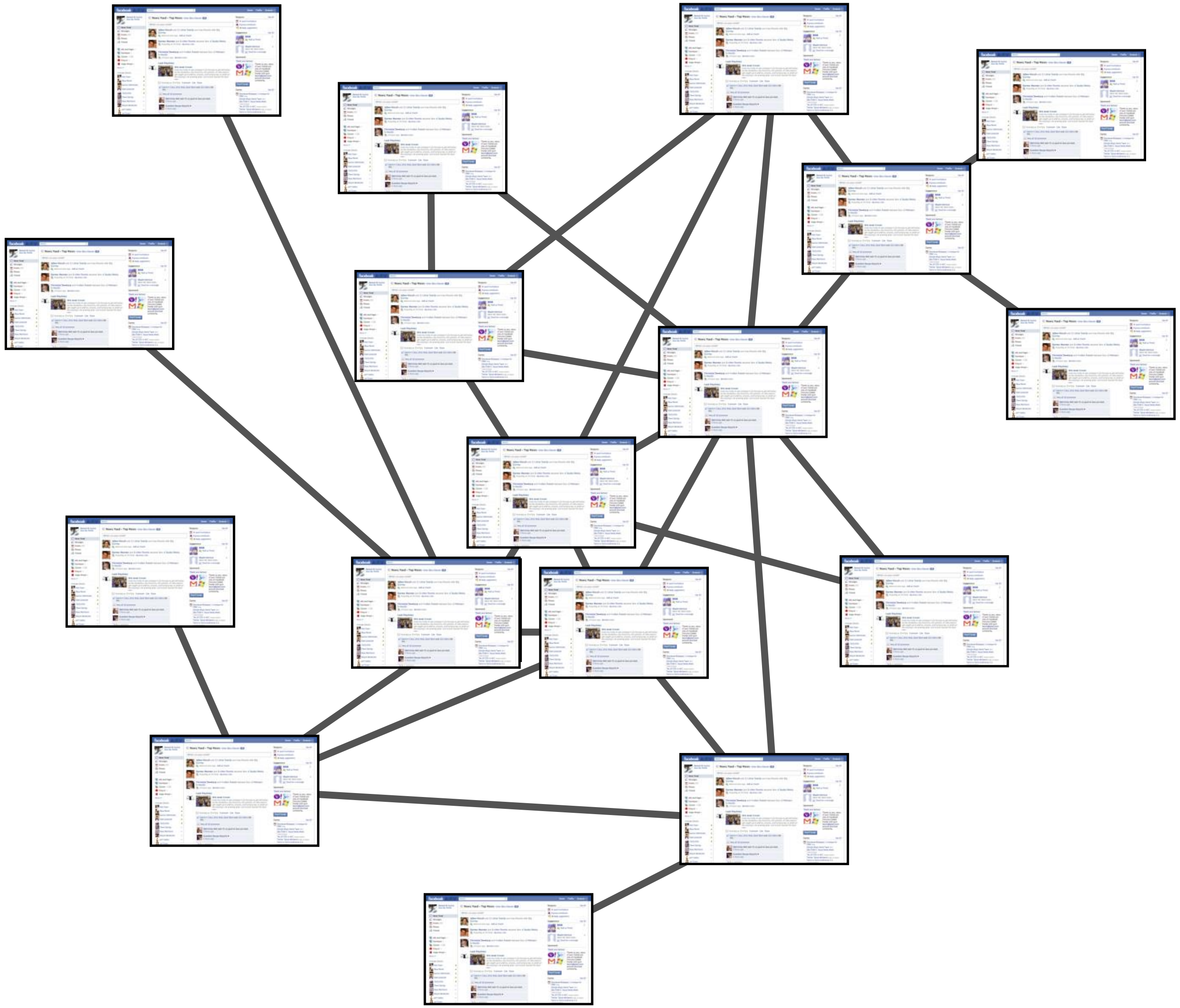
# Interference motivation

- Experimentation goal: ultimately, we want to measure – “what will happen if I launch this product for *everyone*, compared to if *everyone* gets the control”
  - *“Global treatment effect”*
- With A/B testing so far, we give some people the treatment and some people the control, and then calculate the treatment effect $Y_1 - Y_0$
- We implicitly assumed: if we give ***some*** people the treatment, individually that is equivalent to giving ***everyone*** the treatment:
  - Effect of giving someone a coupon doesn’t depend on if their friend got a coupon
- This assumption is often violated in people-centric systems!
  - (Social) network effects, capacity constraints
- Different *units* (people) *interfere* with one another

# Interference in experimentation

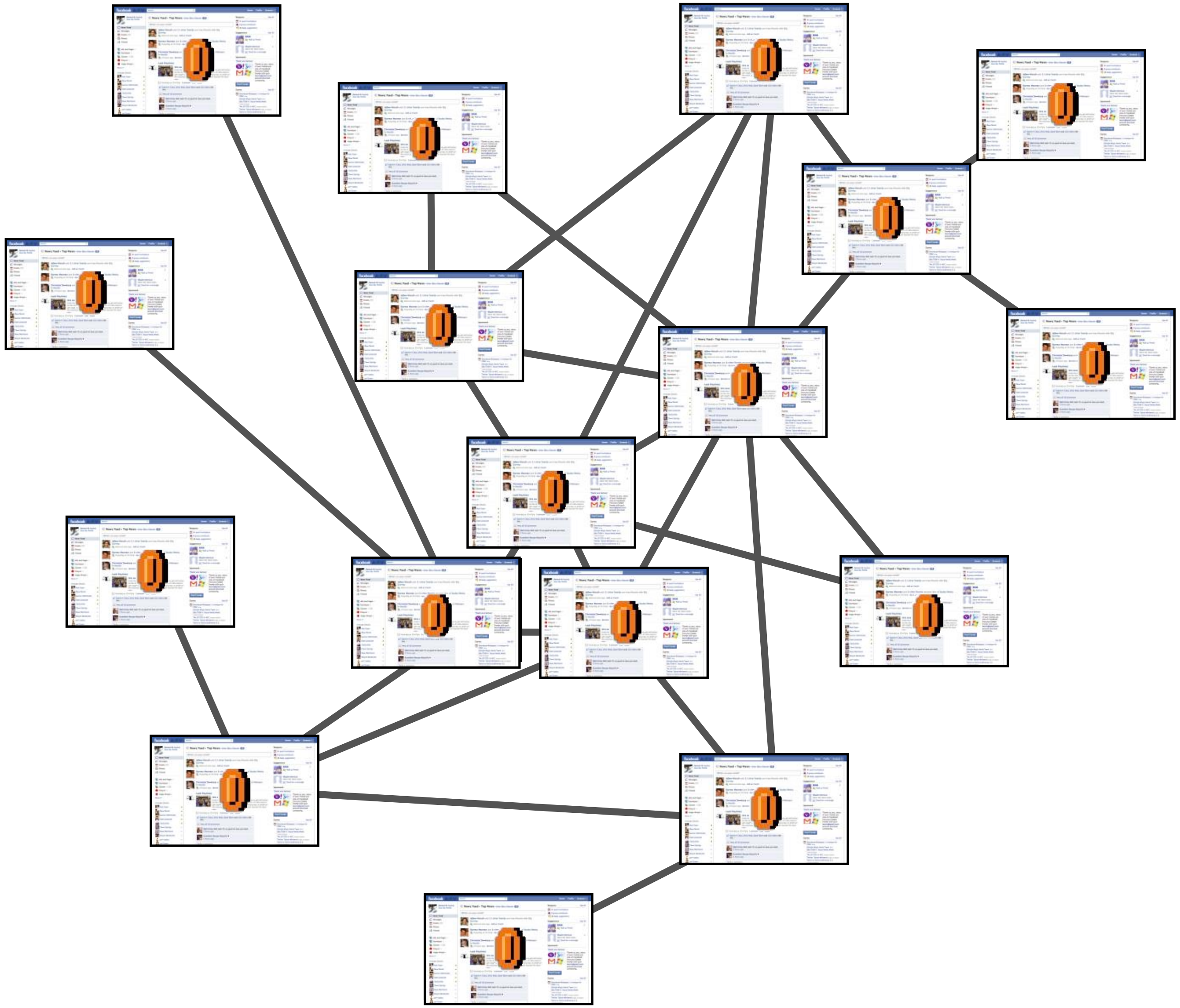
A/B testing in (social) networks

# A/B testing under network effects



Slide credit: Johan Ugander, Stanford

# A/B testing under network effects



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# A/B testing under network effects

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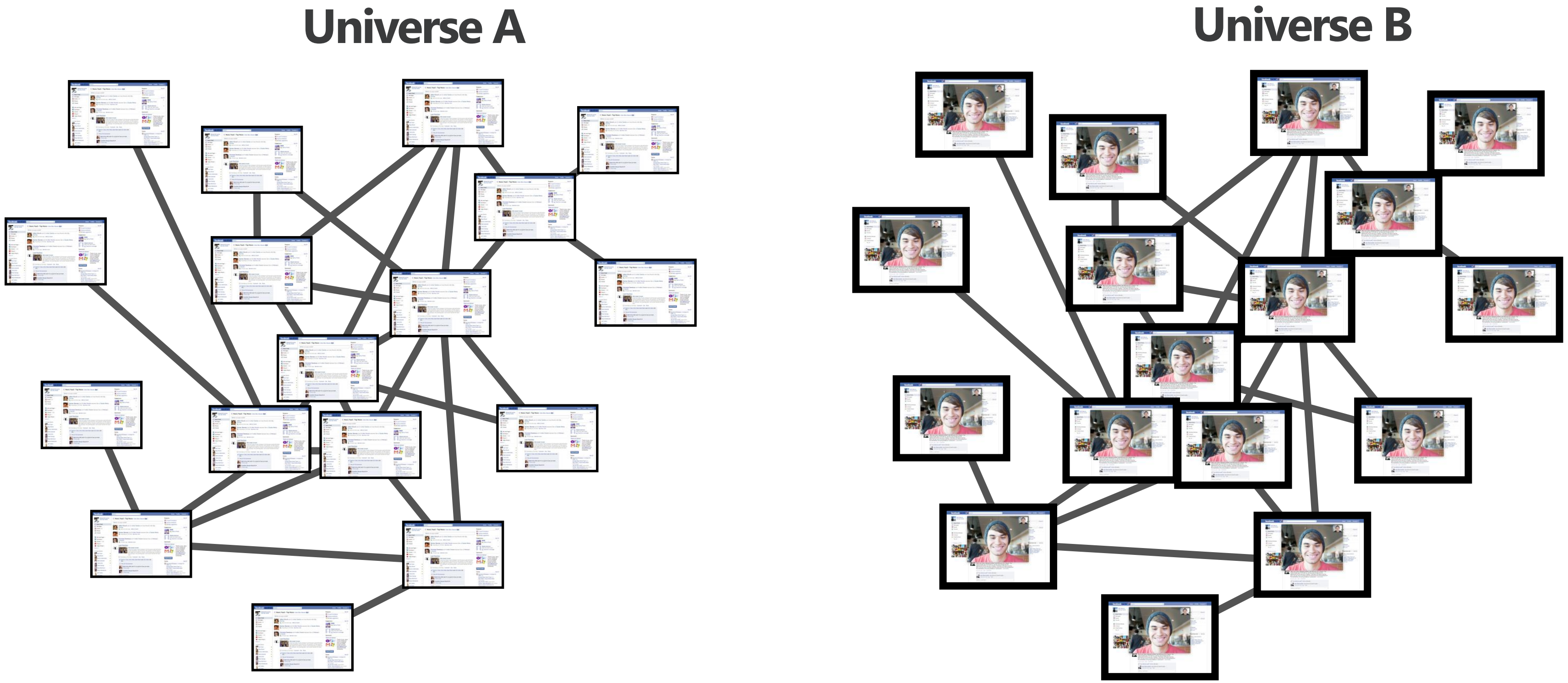
# Causal inference & network effects

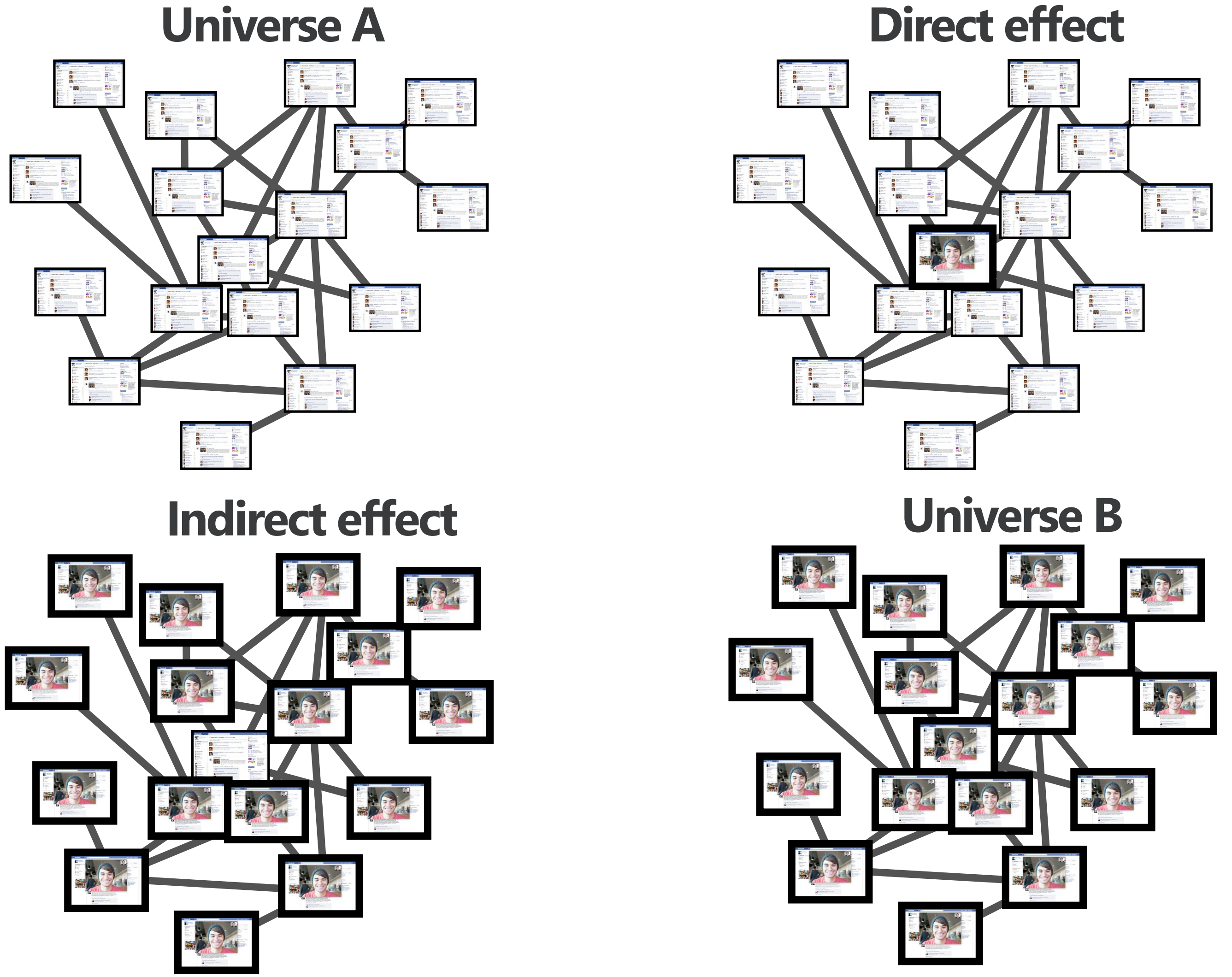



**Fundamental problem: want to compare (average treatment effect, ATE), but can't observe network in both states at once.**


- 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.


Slide credit: Johan Ugander, Stanford

# Direct vs. indirect effects

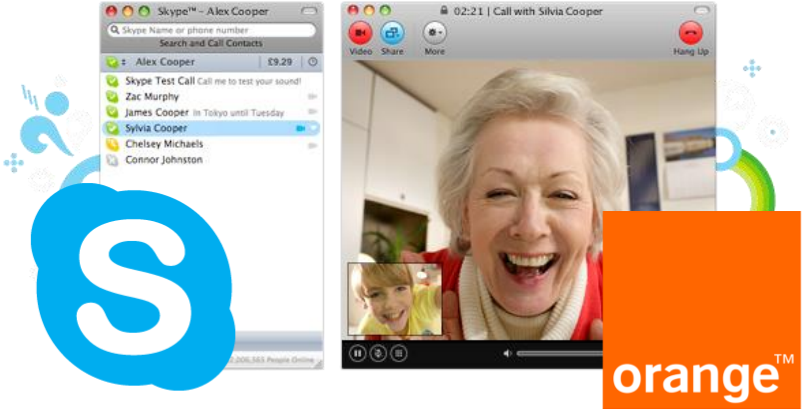



- P Aronow, C Samii (2013) "Estimating average causal effects under interference between units," arXiv.
- C Manski (2013) "Identification of treatment response with social interactions," The Econometrics Journal.

Slide credit: Johan Ugander, Stanford

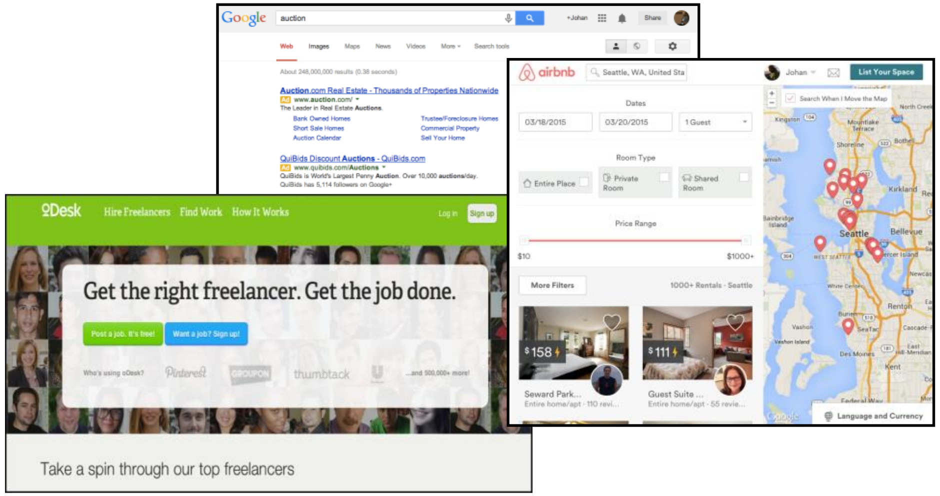
# Experiments with interference

## Chat/communication services

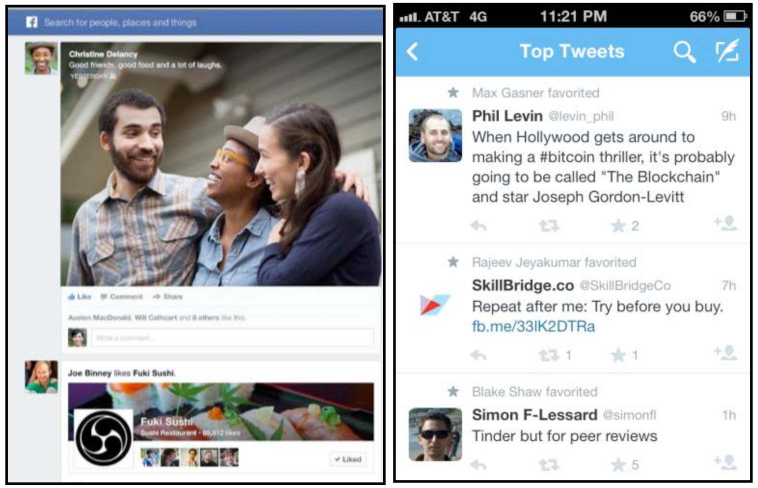


## Social product design

## Market Mechanisms (ads, labor, etc)




## Content ranking models

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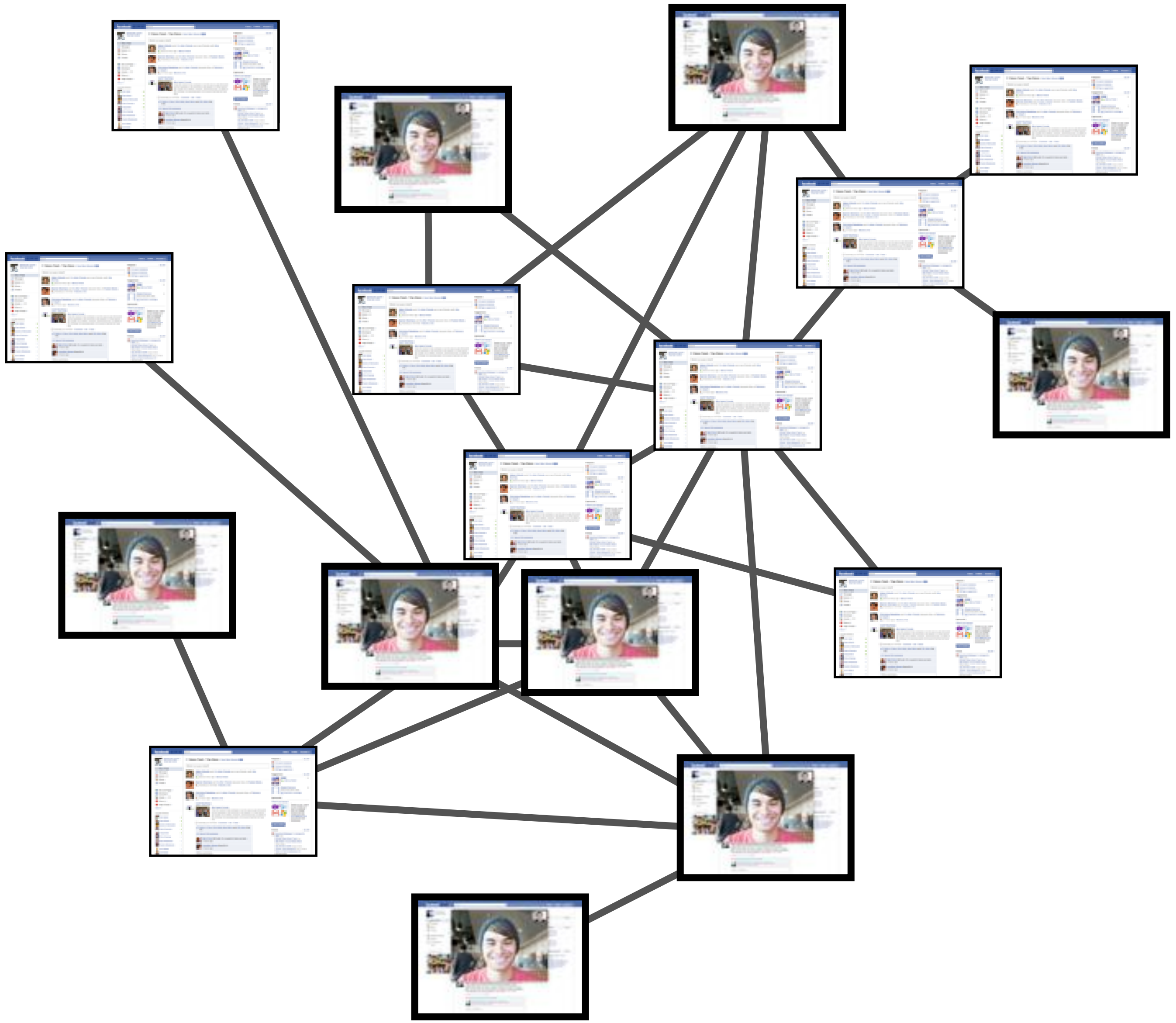
# Design & Analysis



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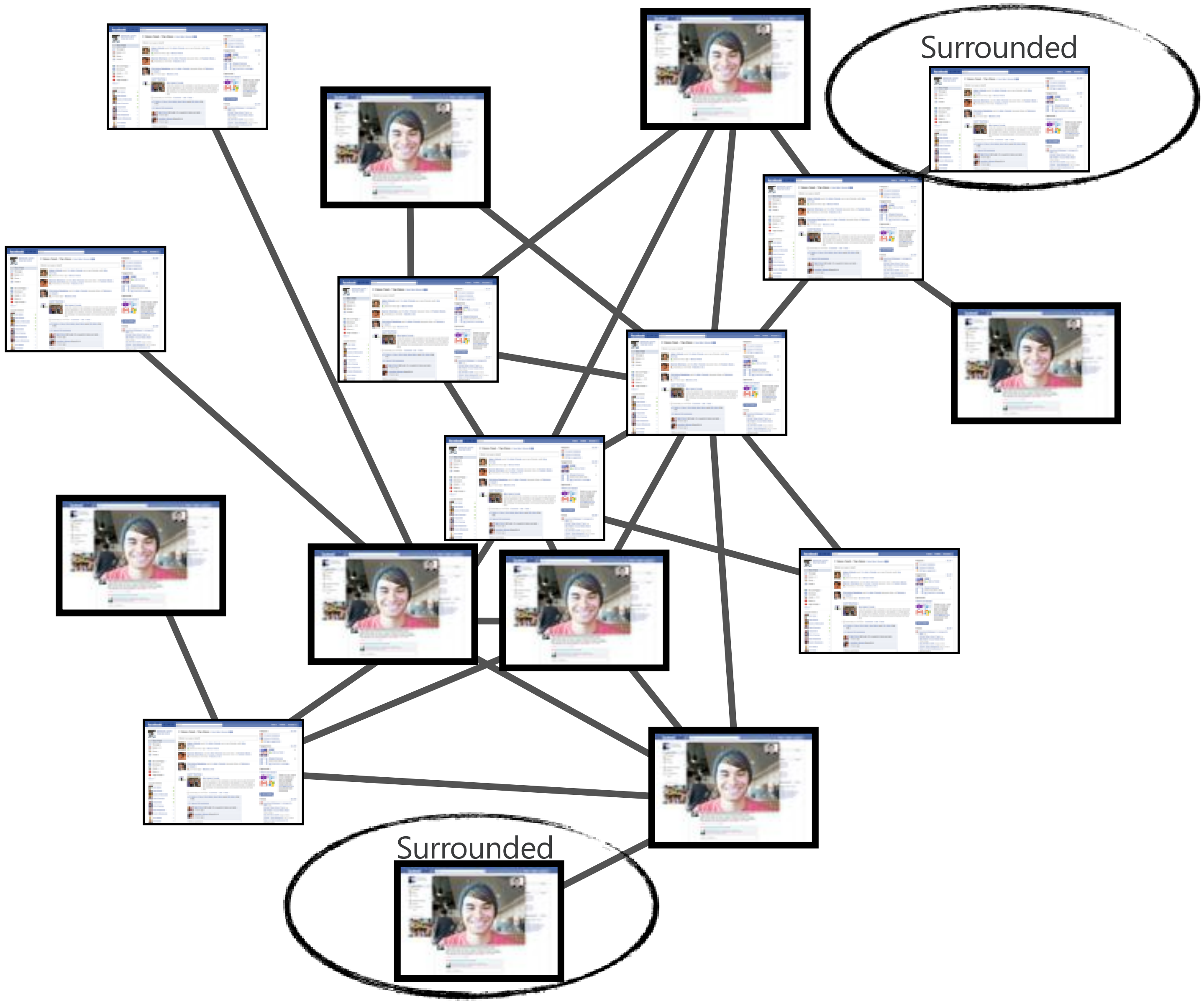
# Design & Analysis

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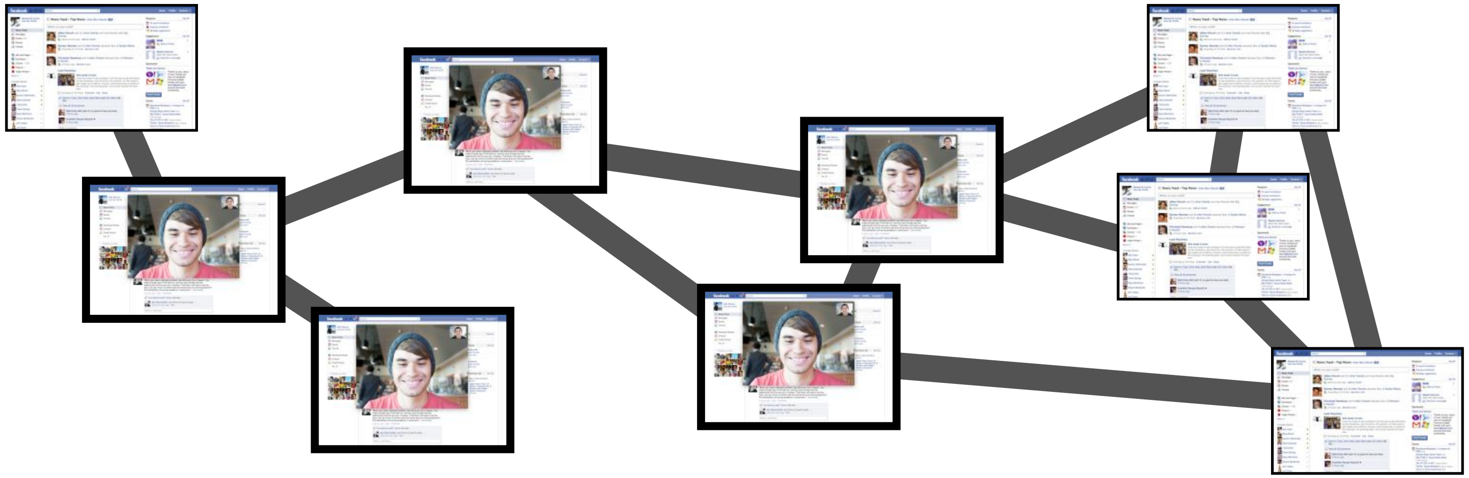
# Analysis: “network exposure”

- 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



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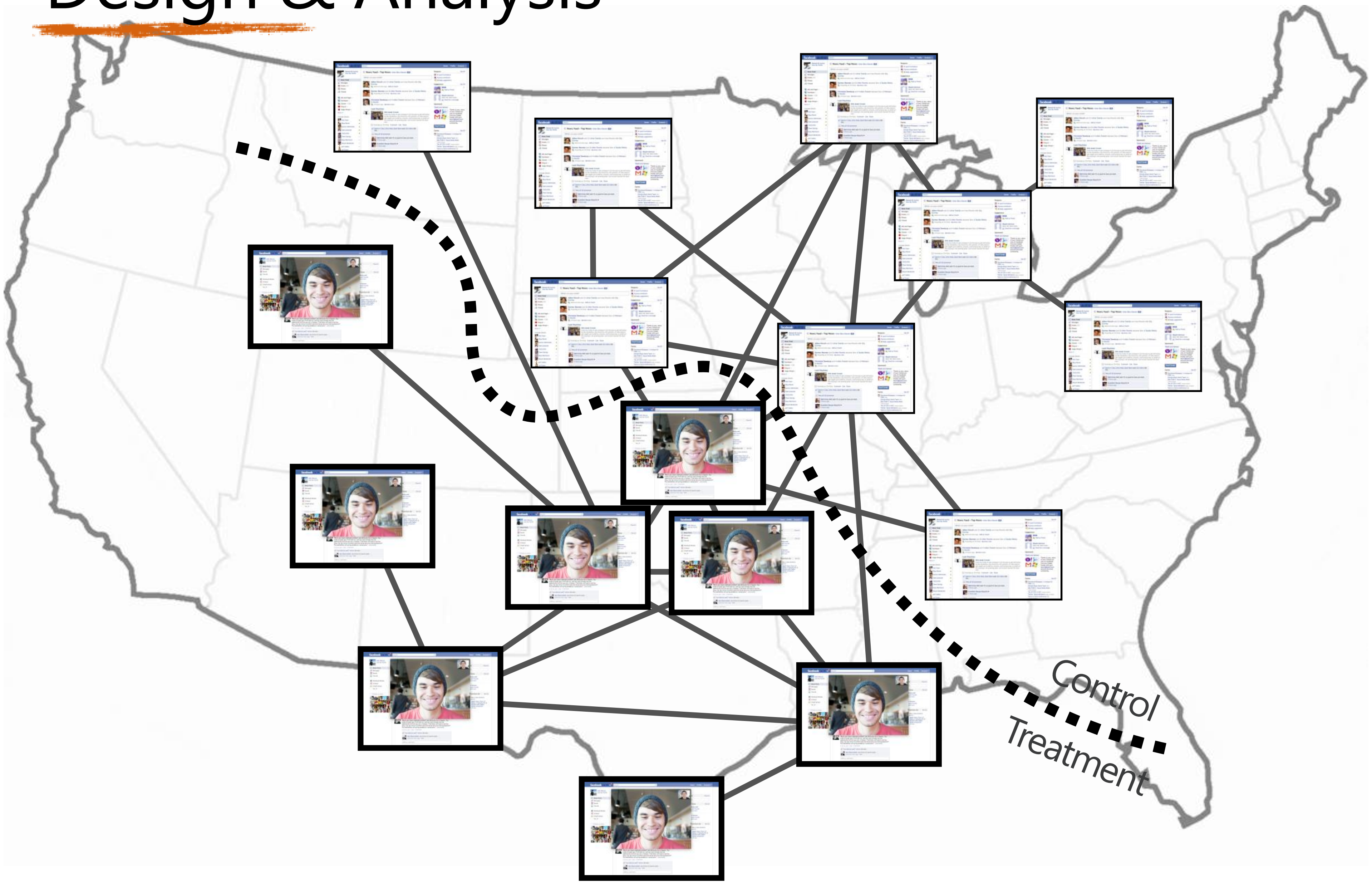



Slide credit:
Johan
Ugander,
Stanford

# New Zealand assignment


Image credit: Johan Ugander, Stanford

Idea: Pick a region of the graph that is densely connected with each other, but less connected with other parts of the graph. Put treatment in region, control everywhere else

# “Graph cluster” randomization

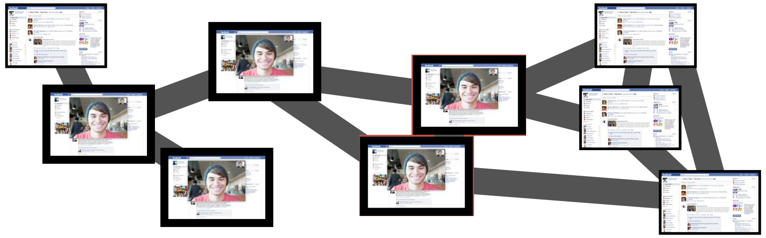
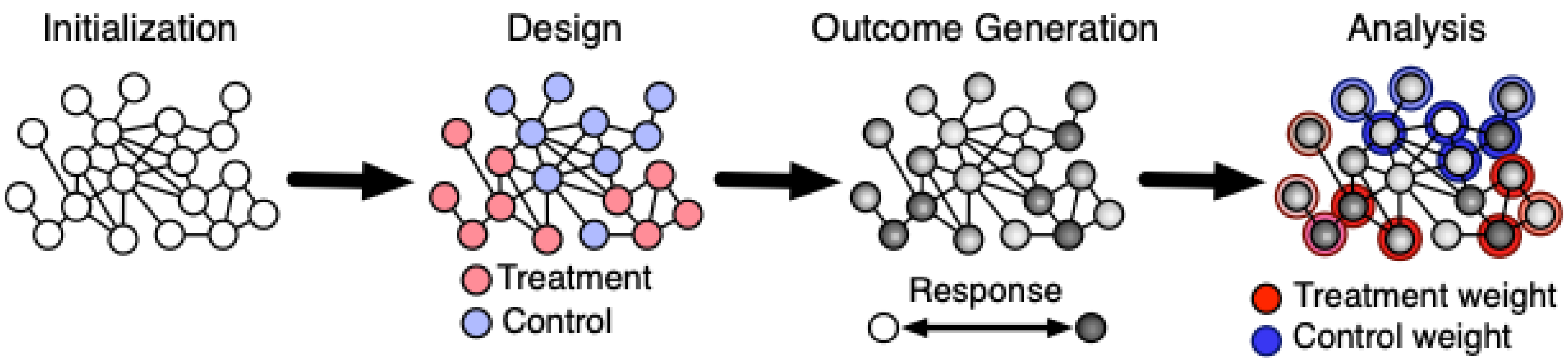



Image credit: Johan Ugander, Stanford

Idea: Algorithmically find many such regions, and then assign half of them treatment, and the other half control

# Network Experimentation summary

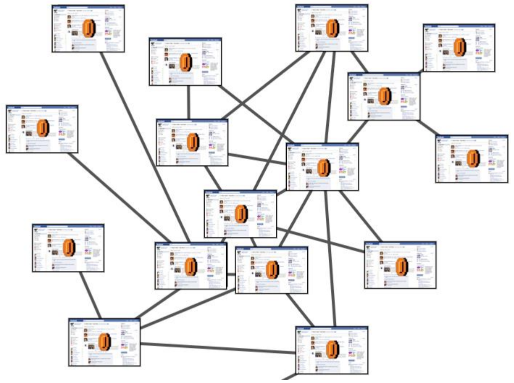



- Initialization: An empirical graph or graph model
- Design: Graph cluster randomization
- Outcome generation: Observe behavior (or observe model)
- Analysis: Discerning effective treatment

Slide credit: Johan Ugander, Stanford

# General lesson: “unit” of randomization

- If you randomize at the “individual” level (each individual is its own “unit”), then treatment and control units can interfere with each other
- Solution is often to change the *unit of randomization*: randomize “clusters” instead of individuals
  - Hope: clusters are *close to independent*
  - If independent, experiment is *unbiased*
- Downside: Experiment “variance” goes down with sample size of experiment
  - Before: Sample size is *millions* (of users)
  - Now: Sample size is *hundreds* (of clusters)
- Same bias-variance trade-off we’ve seen before!

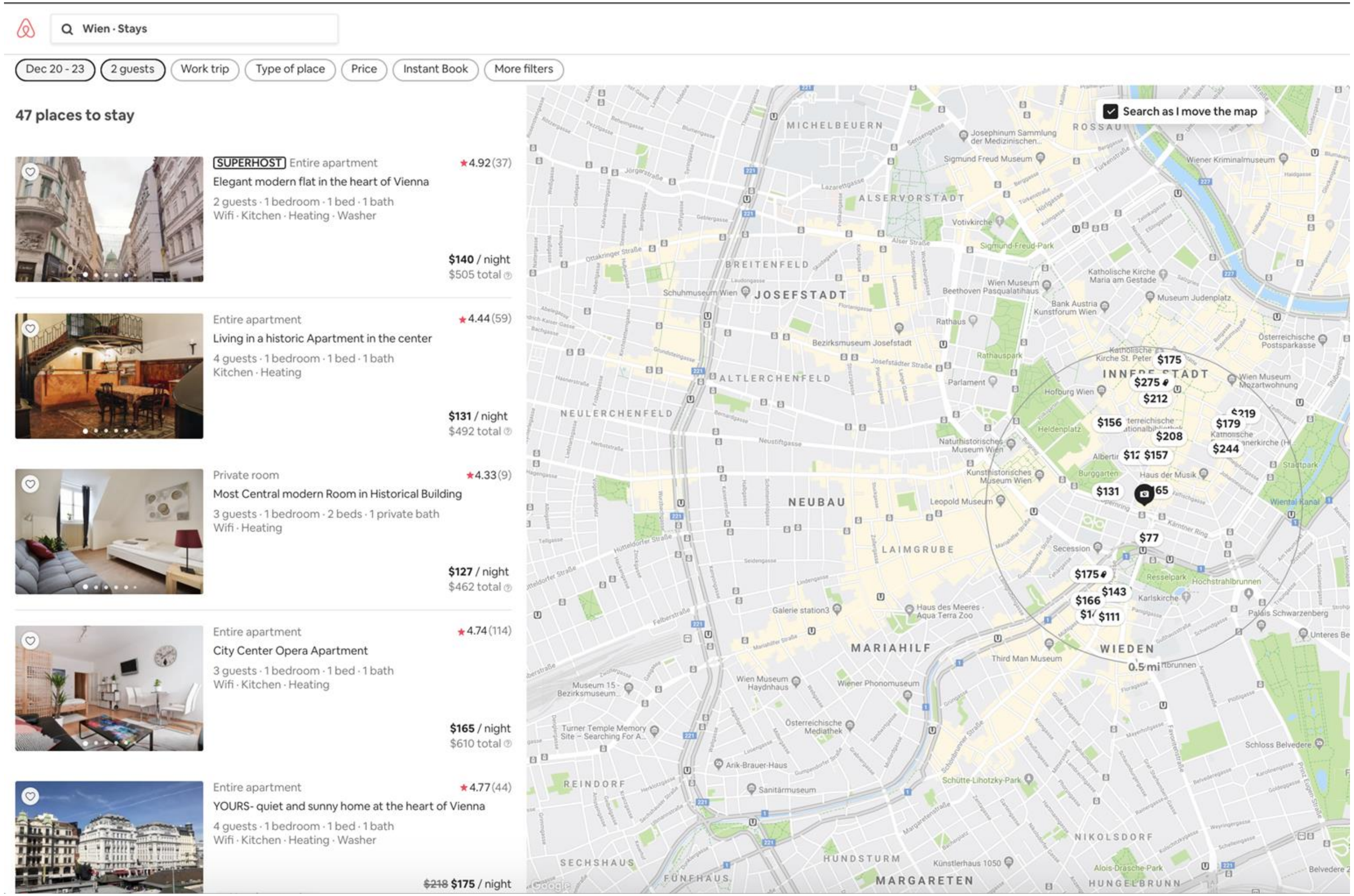


# Interference in marketplaces

- Interference between treatment and control also arises in marketplaces
- In social networks: Interference because use case is *social* – me getting video messaging doesn't matter if none of my friends get it
- In markets, interference rises from *competition and capacity constraints*
- If I make half the products cheaper, customers will *increase* their purchases of the cheaper items…why?
  - *Decrease* their purchases of the more expensive items (**cannibalization**)
  - Go from not purchasing at all, to buying the now cheaper item (**new customer**)
- *Not* a good representation of what would happen if I make *all* my products cheaper

  *Cannibalization effect would not occur; only attraction of new customers*
- Tonight and next time: experimentation in marketplaces under interference

# Example: price change experiment on Airbnb




Slide credit:
Dave Holtz,
UC Berkeley

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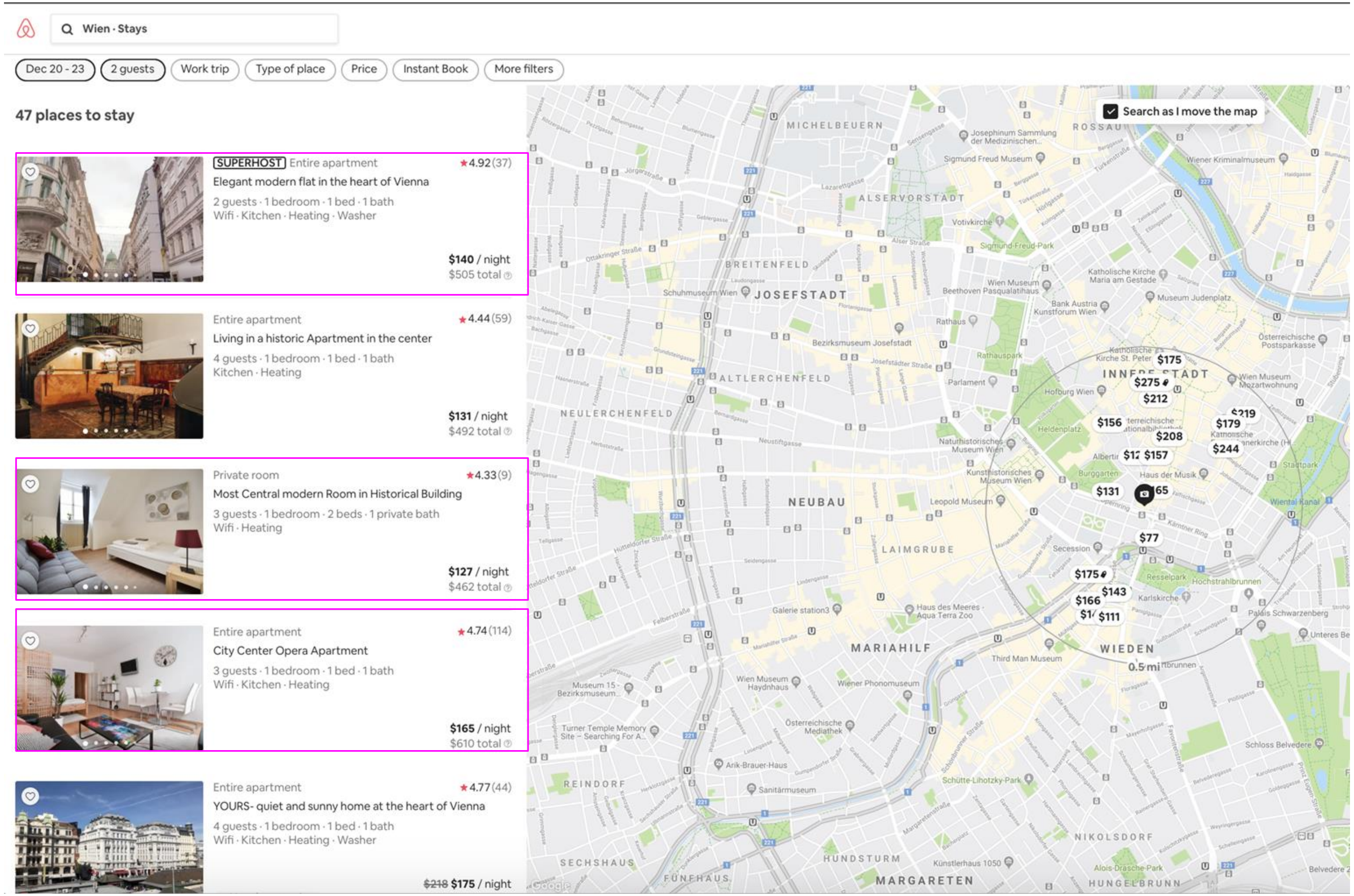
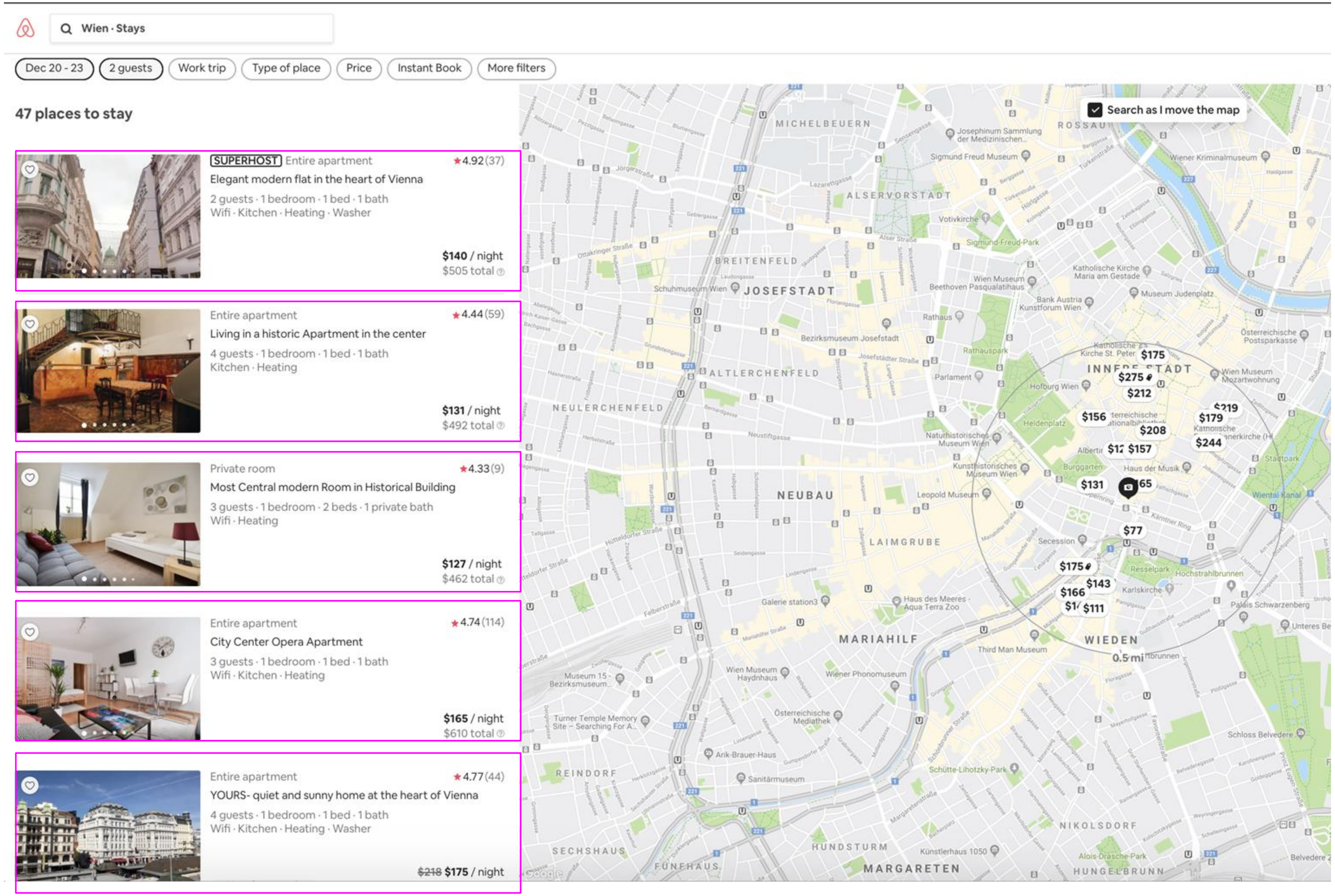



If lower fees on half of the listings, bookings for those listings ↑ 3% ☺

Slide credit: Dave Holtz, UC Berkeley

# Example: price change experiment on Airbnb




If lower fees on all the listings,

Overall bookings flat ☹

Slide credit: Dave Holtz, UC Berkeley

# Approach 1: transform the marketplace into a network

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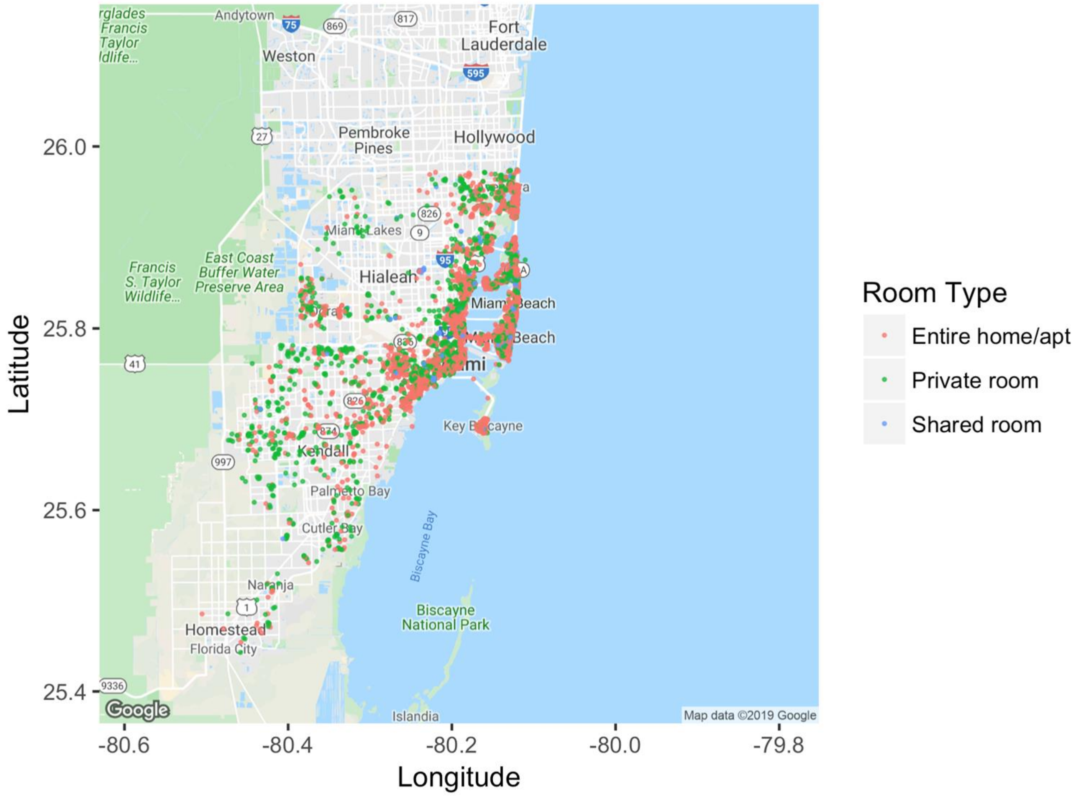


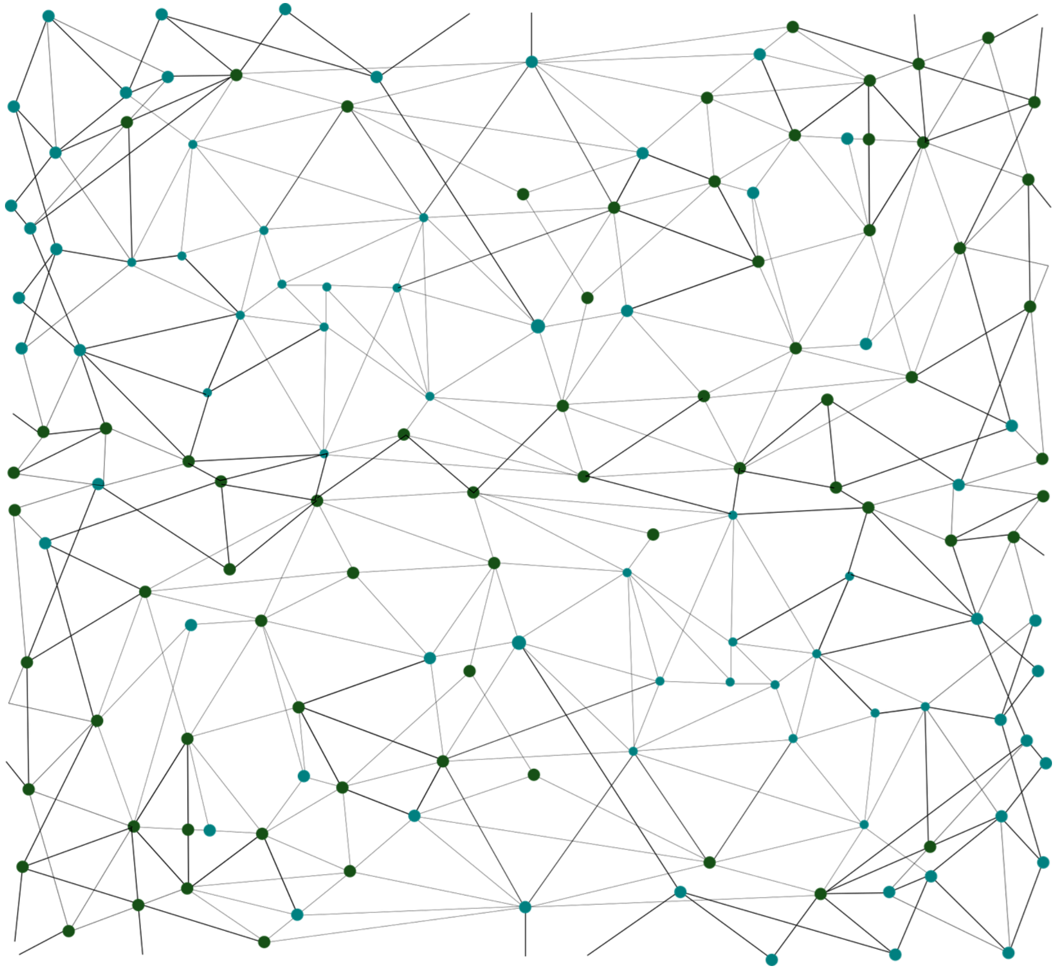
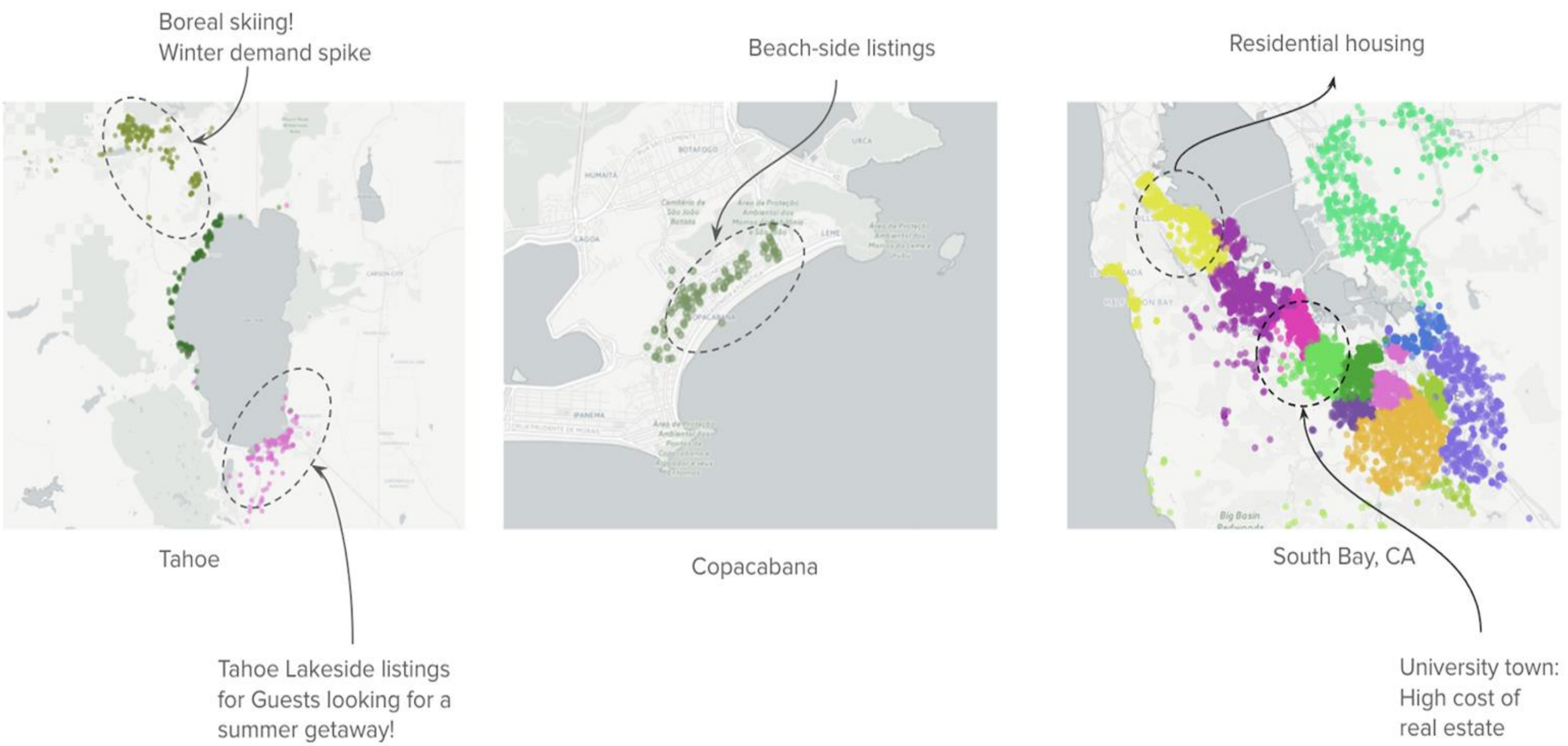



Image source

# Network experiment designs + analysis techniques

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- Now, listings are connected if they tend to be *substitutes*
- Much more complicated to learn the network structure
- Once have network structure, use cluster randomization techniques from above

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