ORIE 5355

Lecture 13: Experimentation complications: peeking and interference

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Experimentation module summary so far

Basics of A/B testing

- Why experimentation?
- Common mistakes in running and analyzing tests

  Peeking

A/B testing in social networks and marketplaces

- Interference between “test” and “control”
- Experiments over networks, space, and time
- Adaptive experimentation

Guest lecture: fill out poll today!

Other topics in causal inference and experimentation

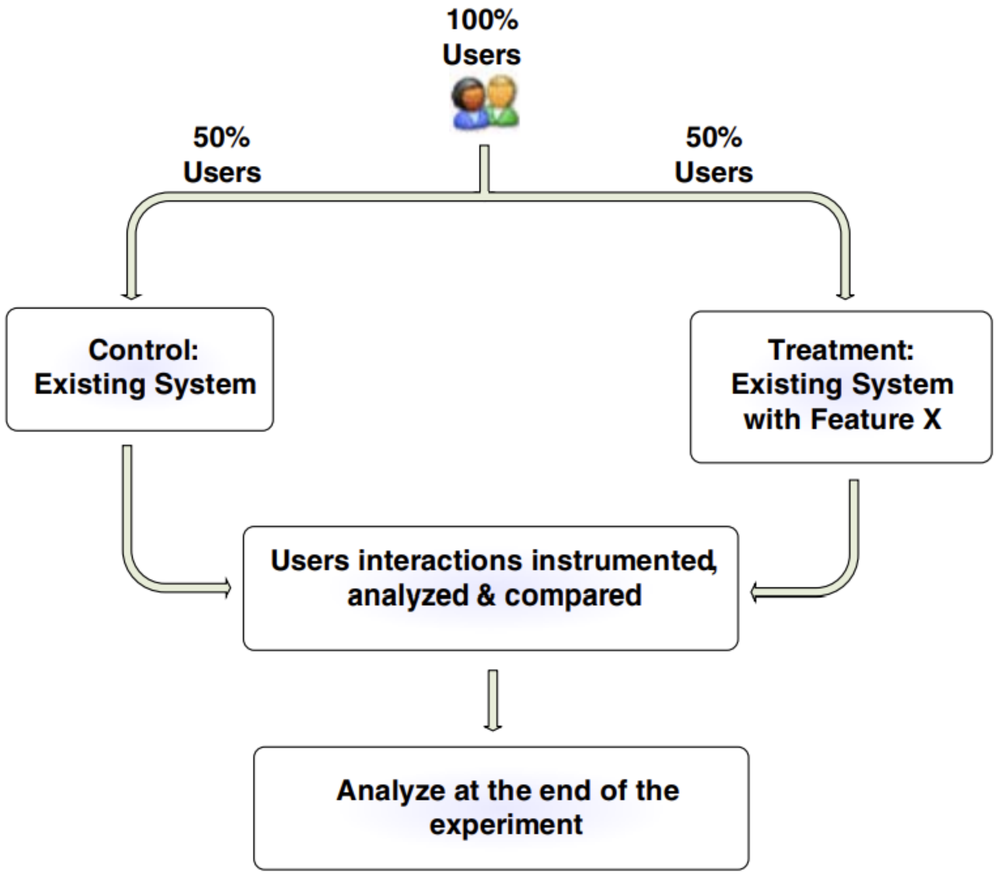
- Causal inference with observational data
- Experimentation culture in companies; making decisions with many experiments over time

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

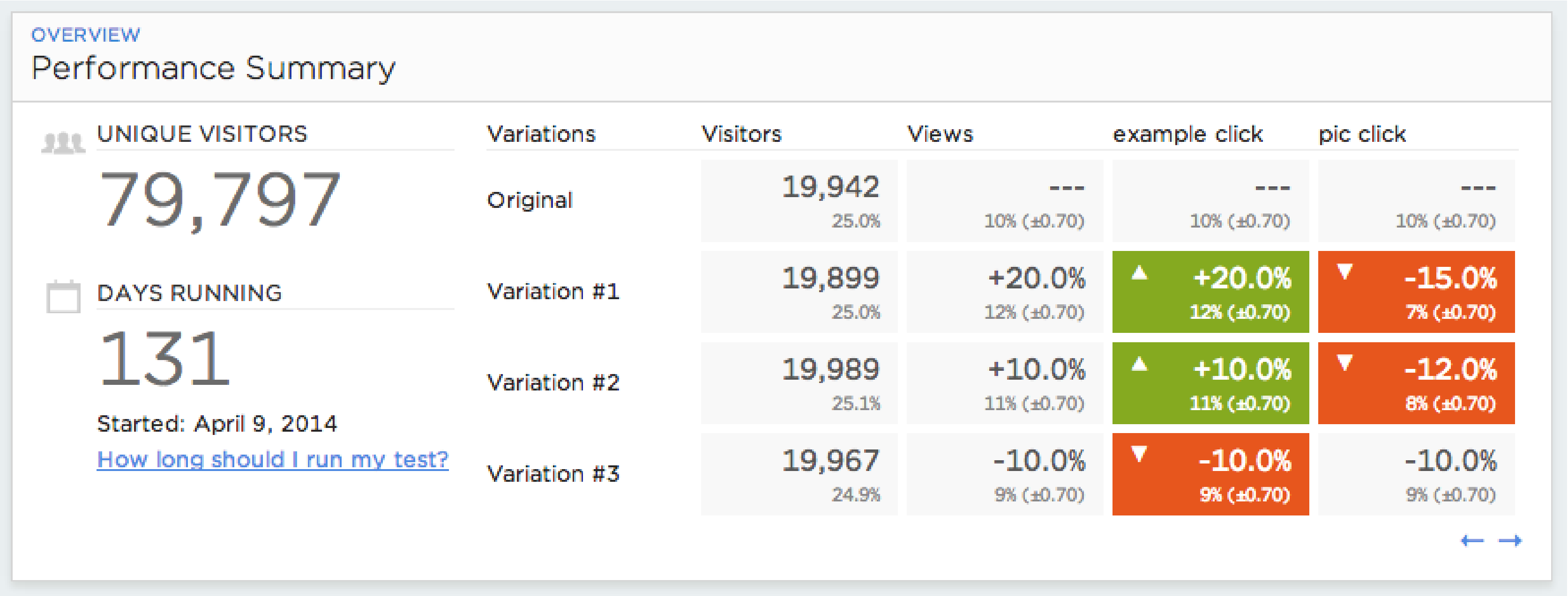


[Source: Controlled experiments on the web: survey and practical guide]

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)]

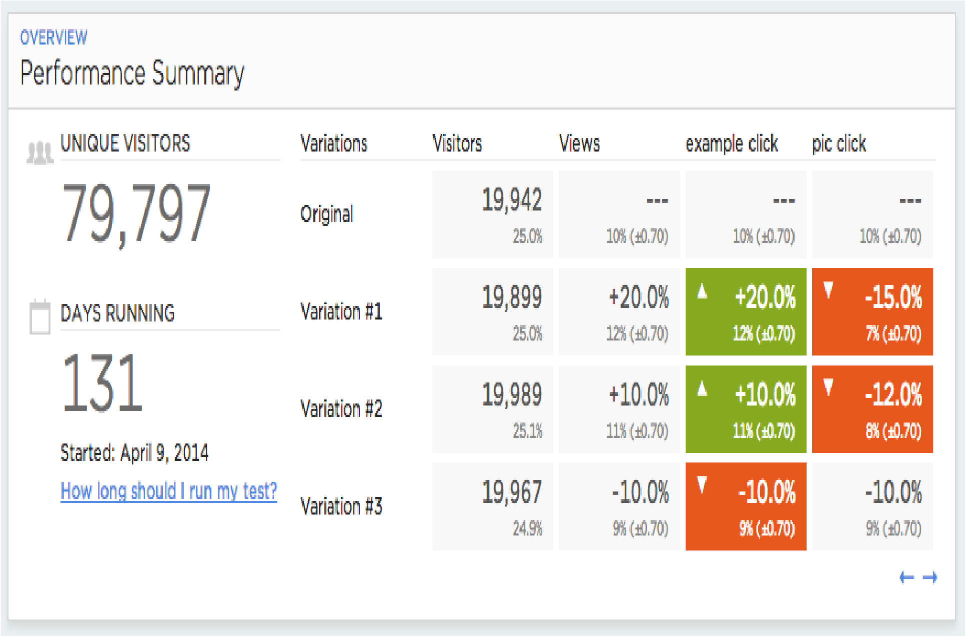
Peeking

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?*

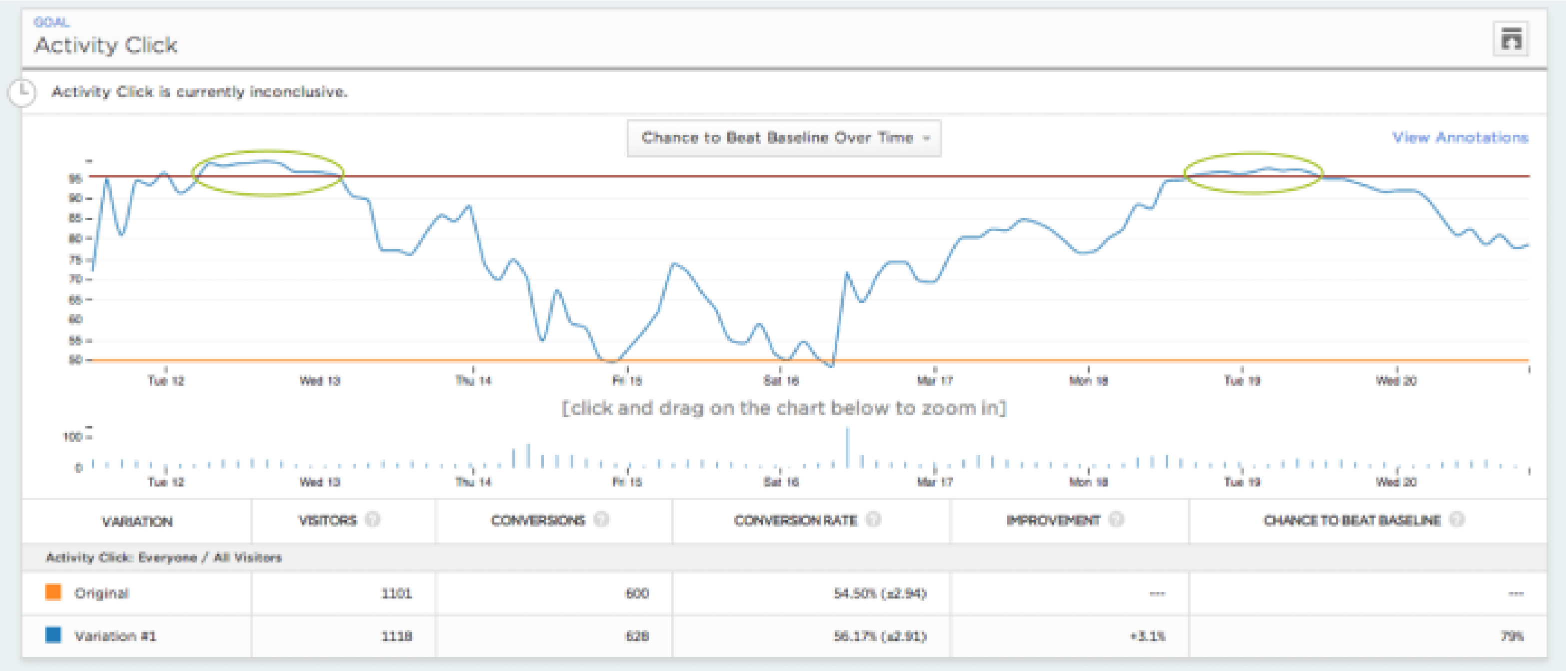
  Remember, $\alpha = 0.05$ means that if there is no true difference ($Y_1 - Y_0 = 0$), then 5% of the time you will falsely declare that $\hat{Y}_1 - \hat{Y}_0 \neq 0$ in a statistically significant way (false positive)

- 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

Design -- 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

Analysis -- Peek, but do **fancy statistics** to make sure p-values are valid

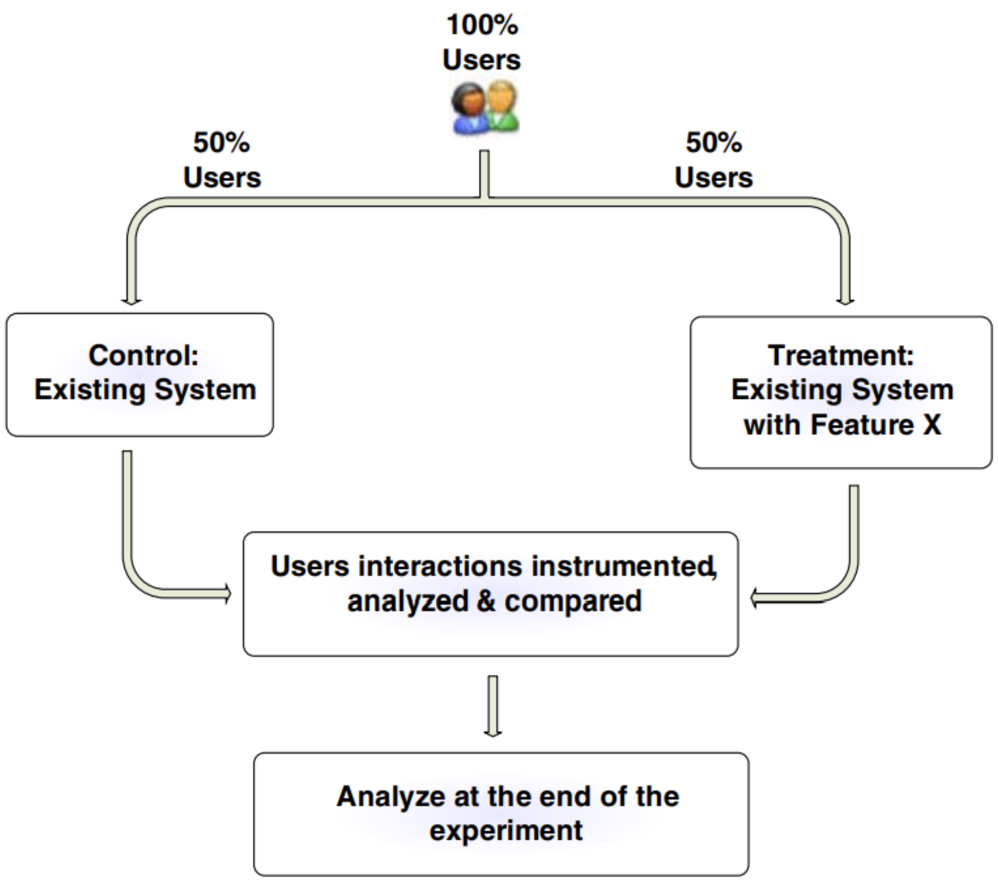
- This is the approach Optimizely implemented on their dashboards
- If you're at a big company with an established experimental culture, they (hopefully) have a dashboard that does this

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]

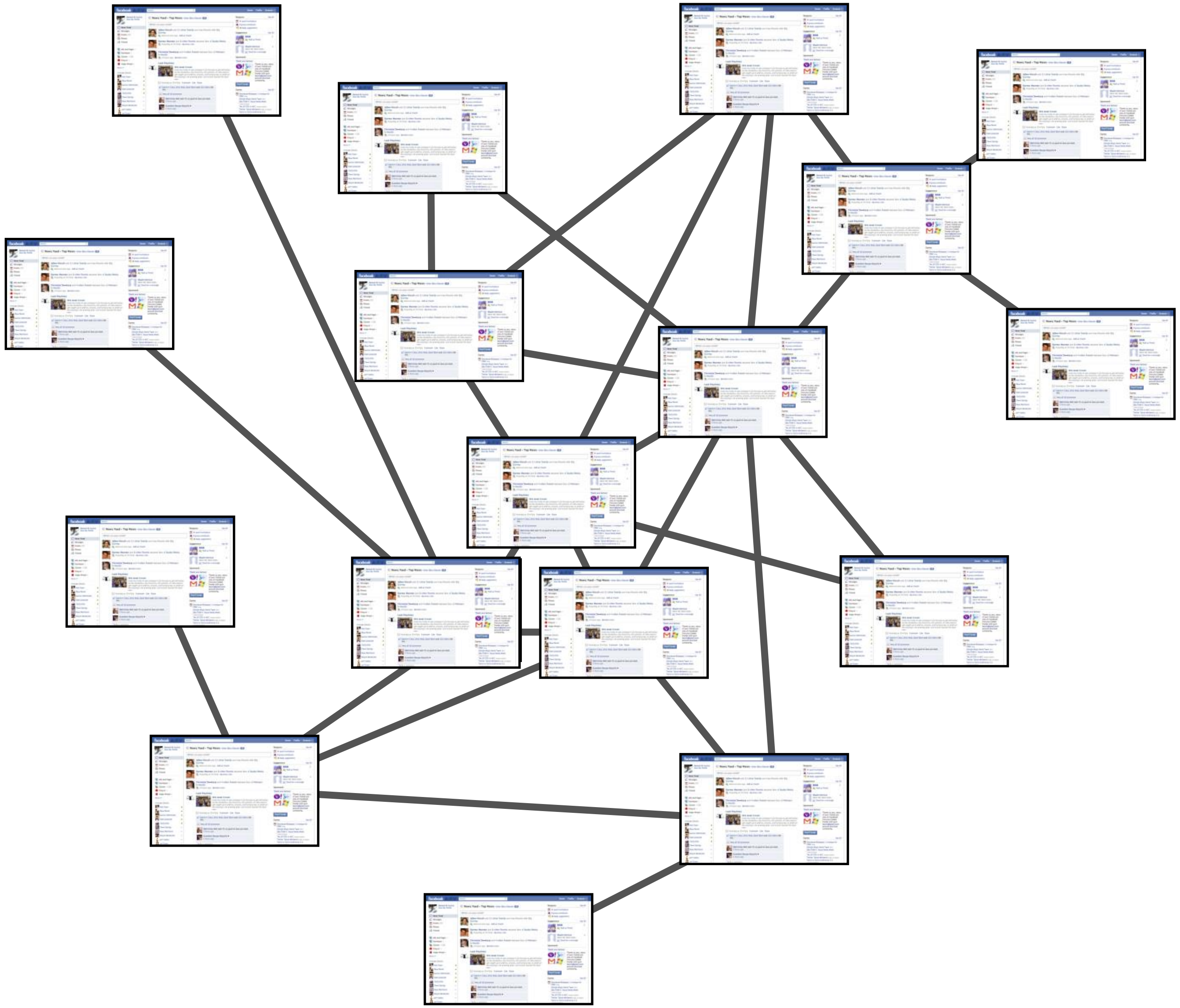
Interference motivation

- 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

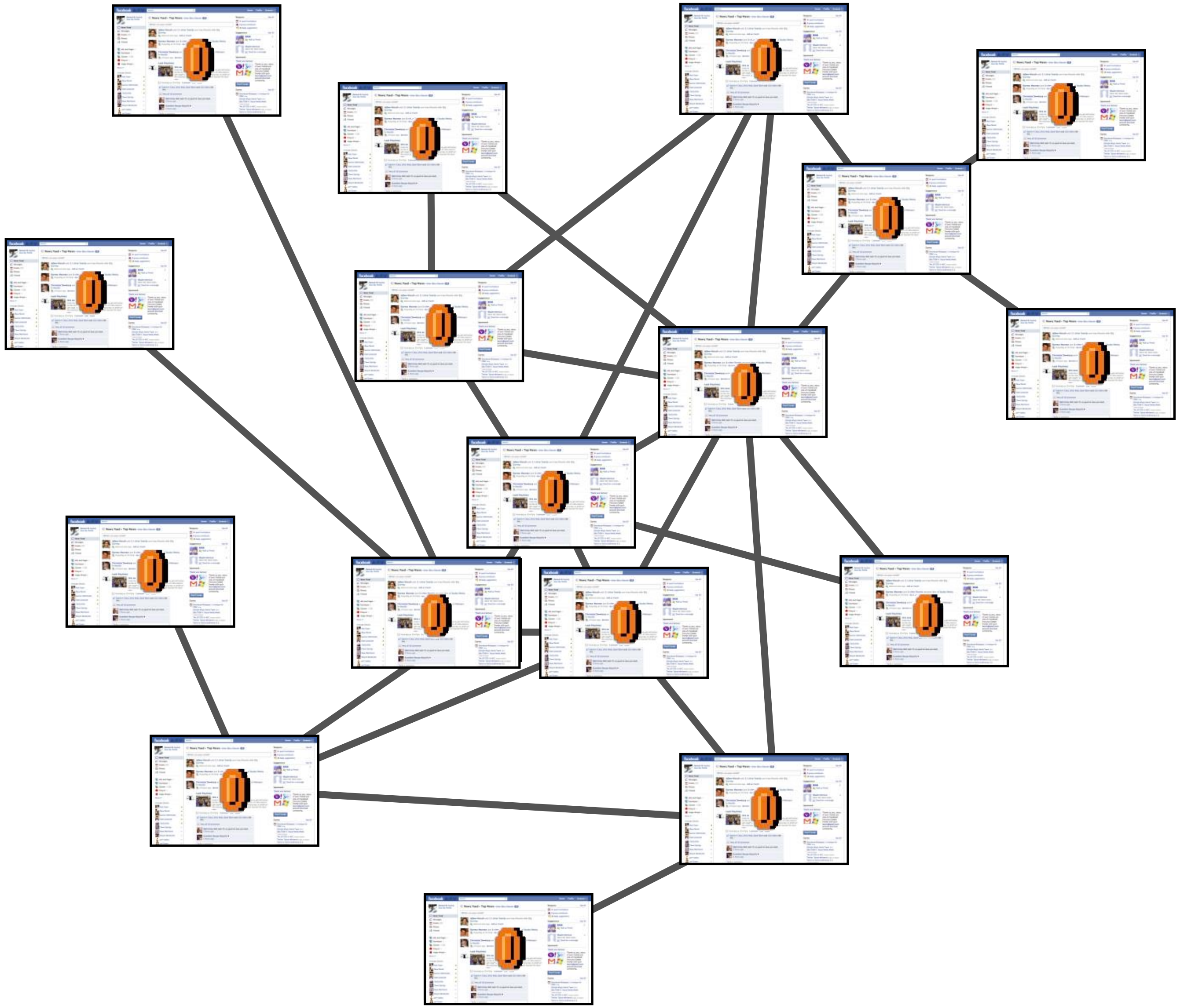
A/B testing in (social) networks

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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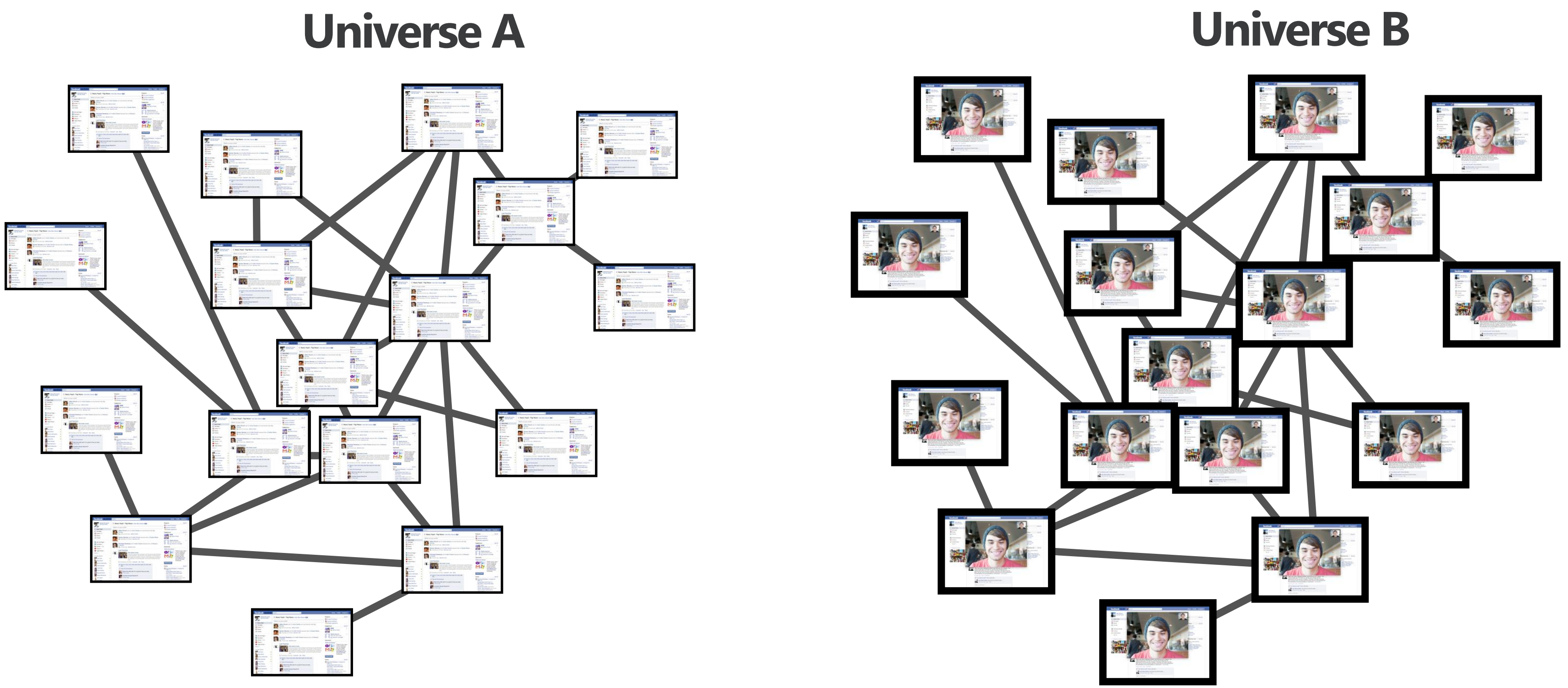
Causal inference & network effects

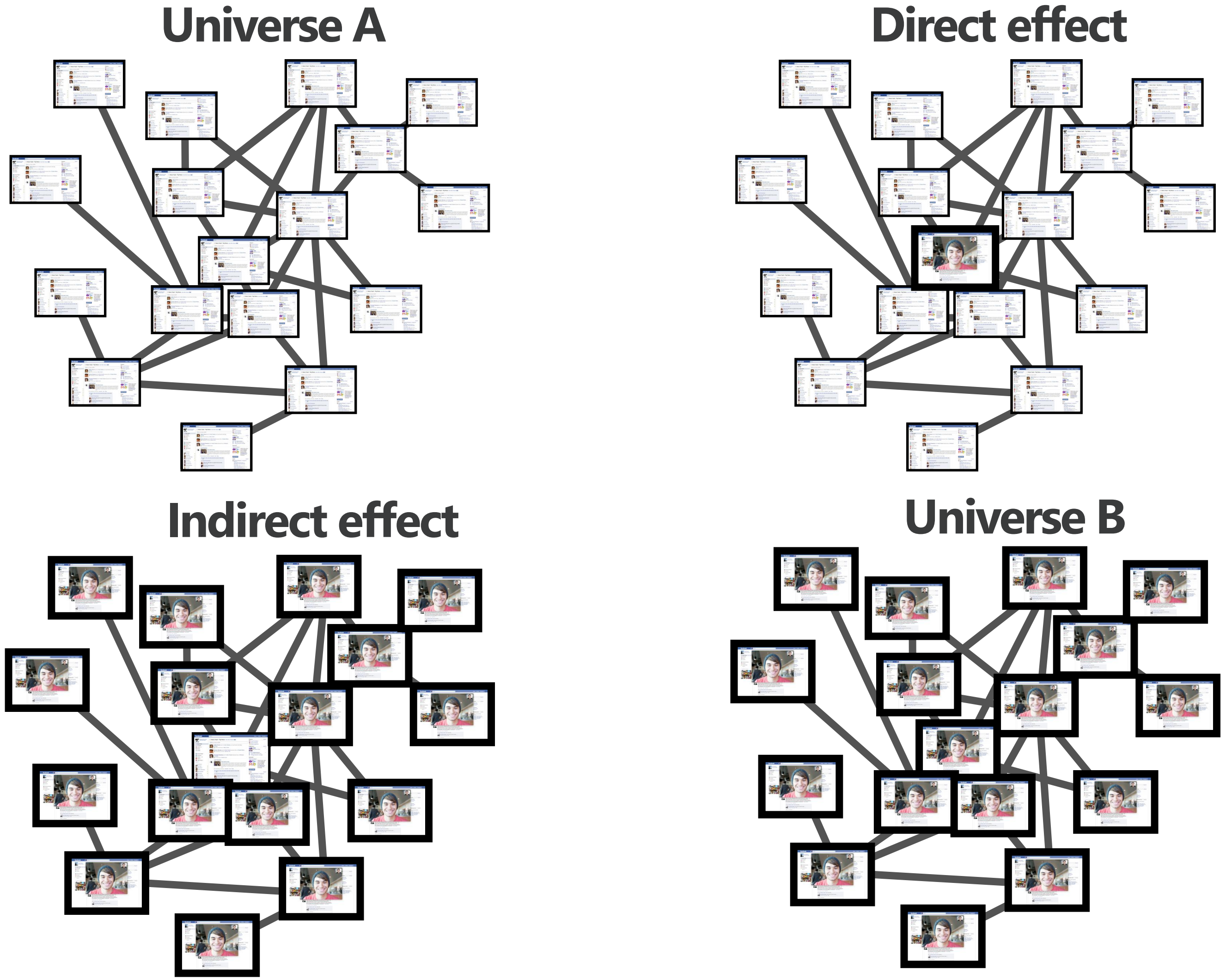


Fundamental problem: want to compare (average treatment effect, ATE), but can't observe network in both states at once.

- 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

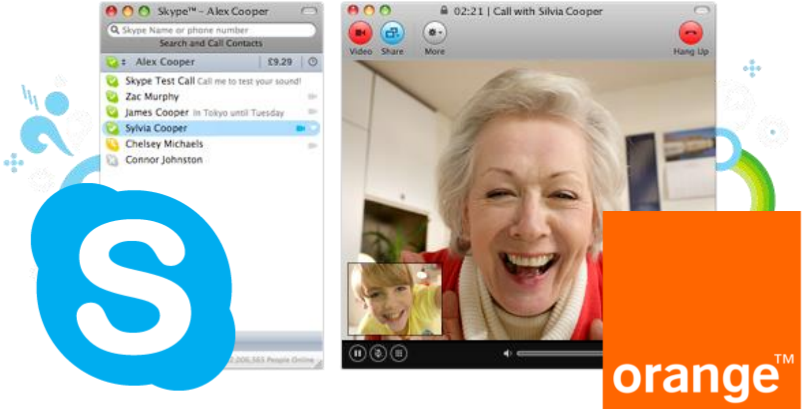


Slide credit: Johan Ugander, Stanford

- 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.

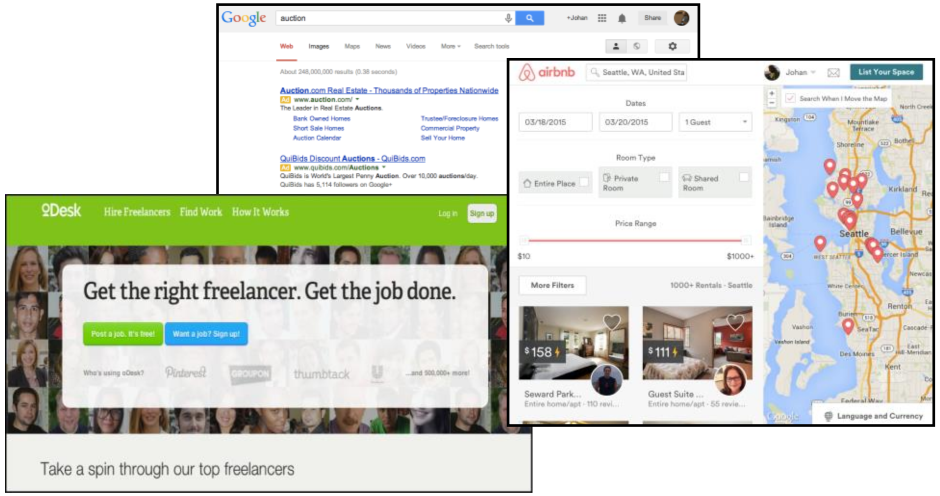
Experiments with interference

Chat/communication services

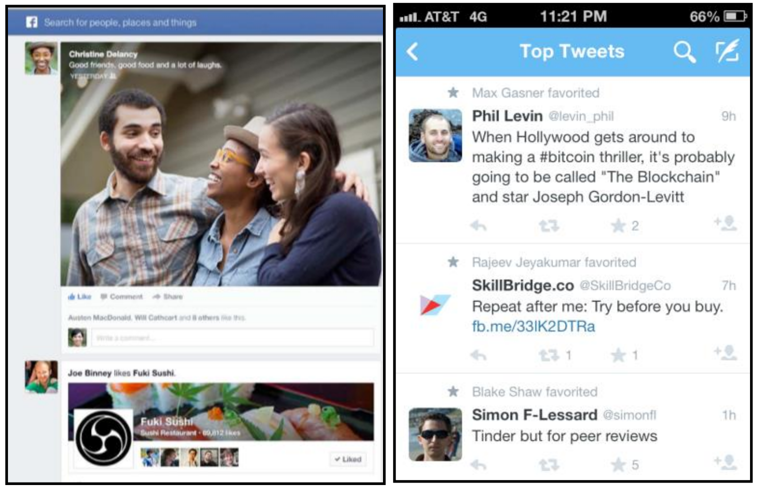


Social product design

Market Mechanisms (ads, labor, etc)



Content ranking models



Slide credit: Johan Ugander, Stanford

Design & Analysis

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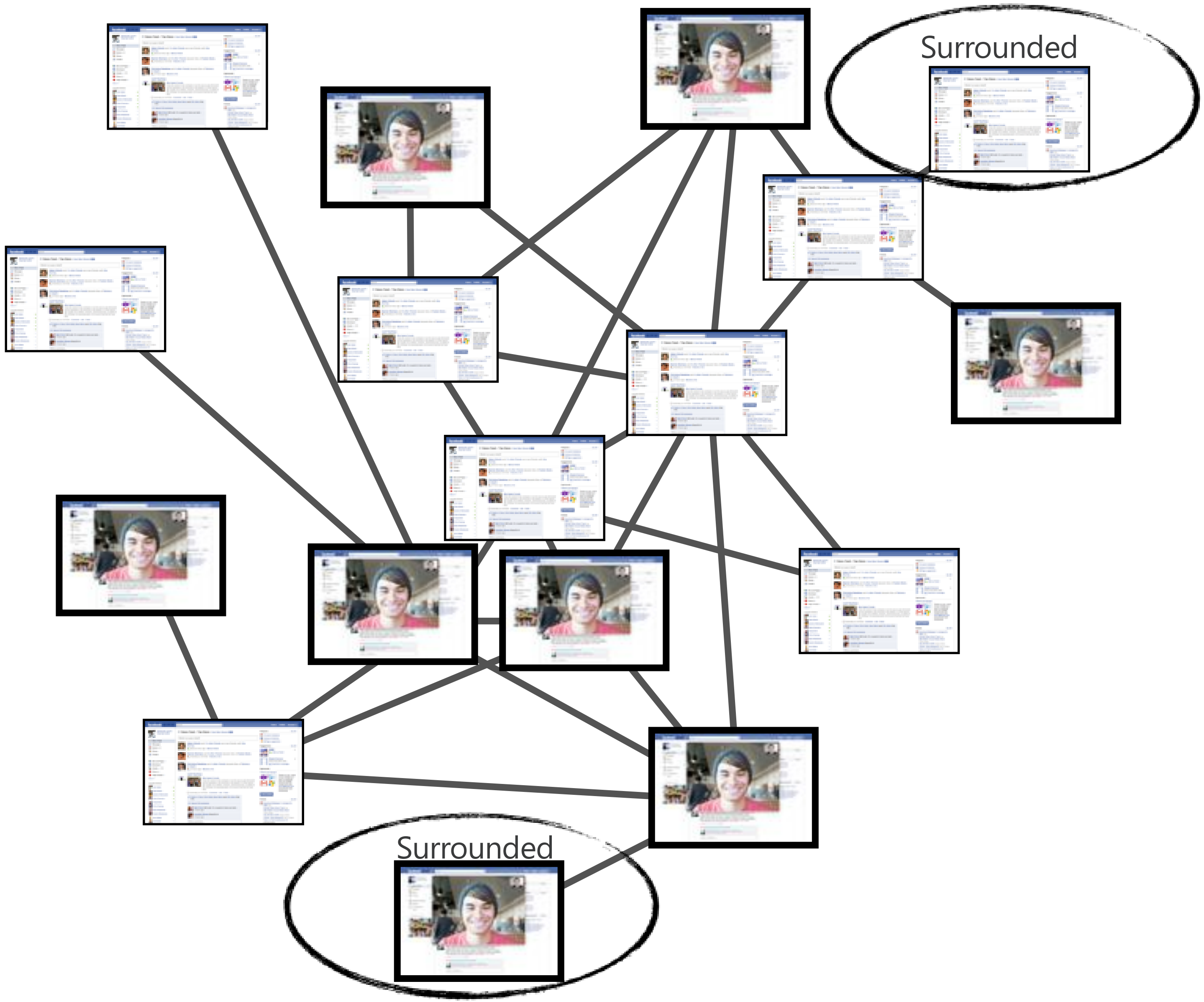
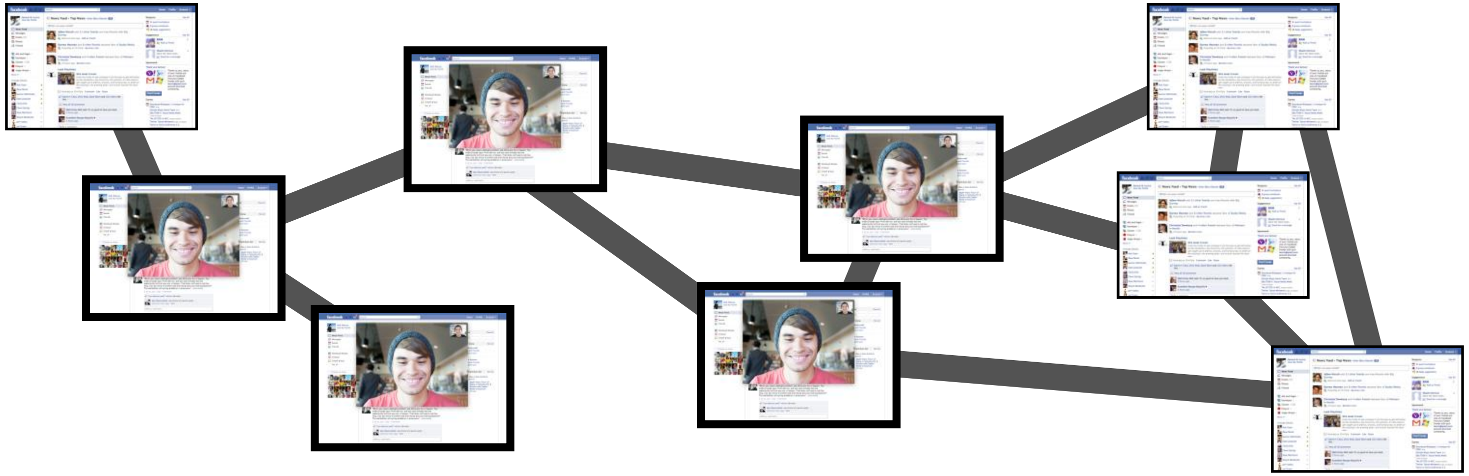
Design & Analysis



Slide credit: Johan Ugander, Stanford

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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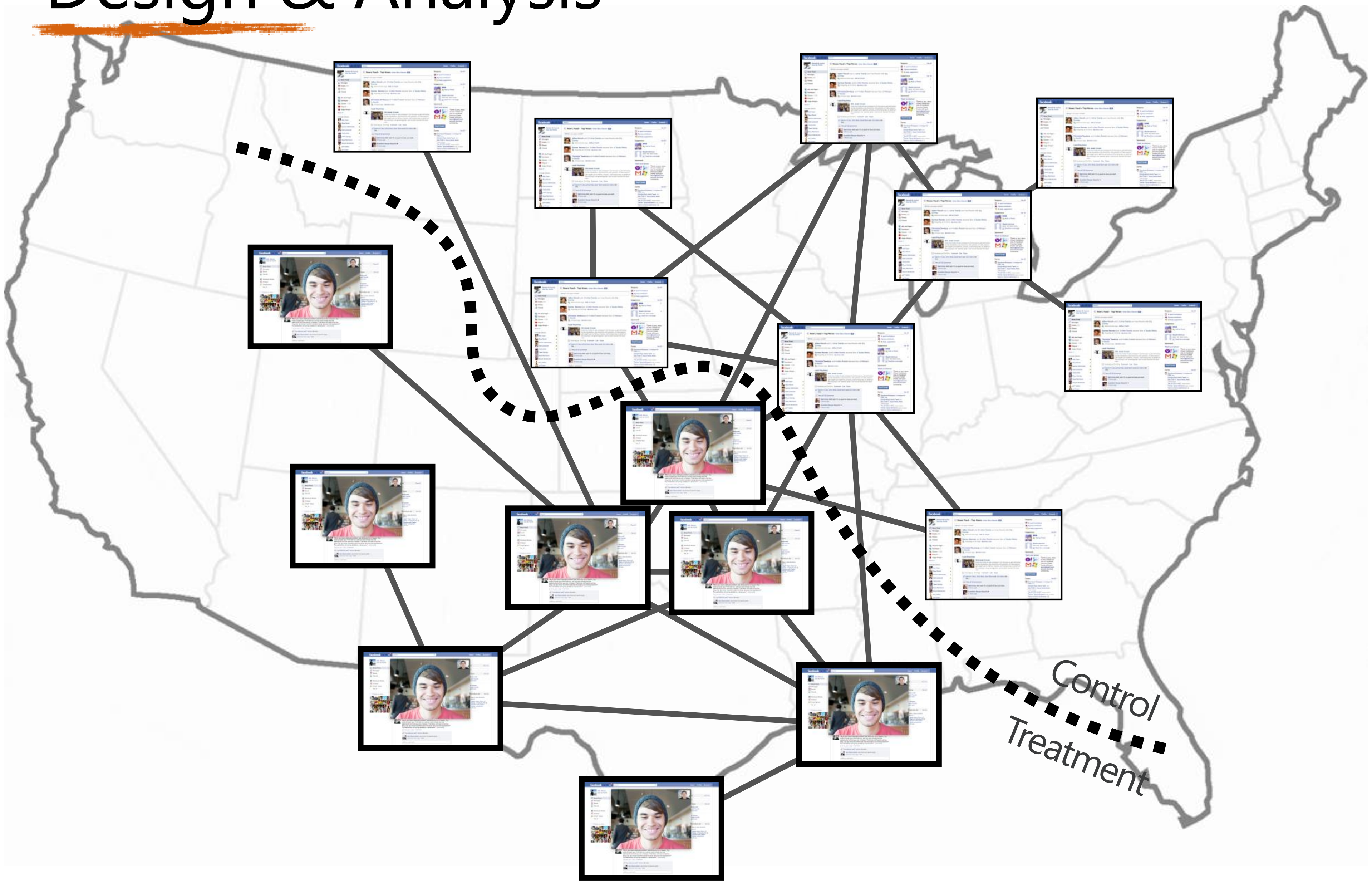
Design & Analysis



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

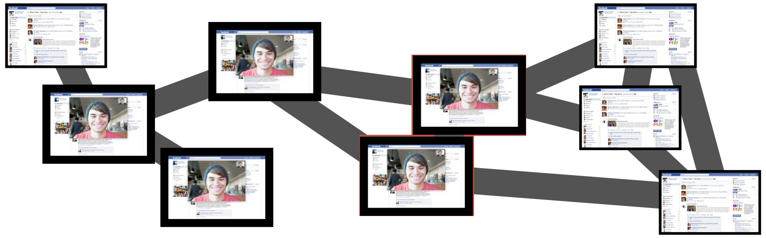
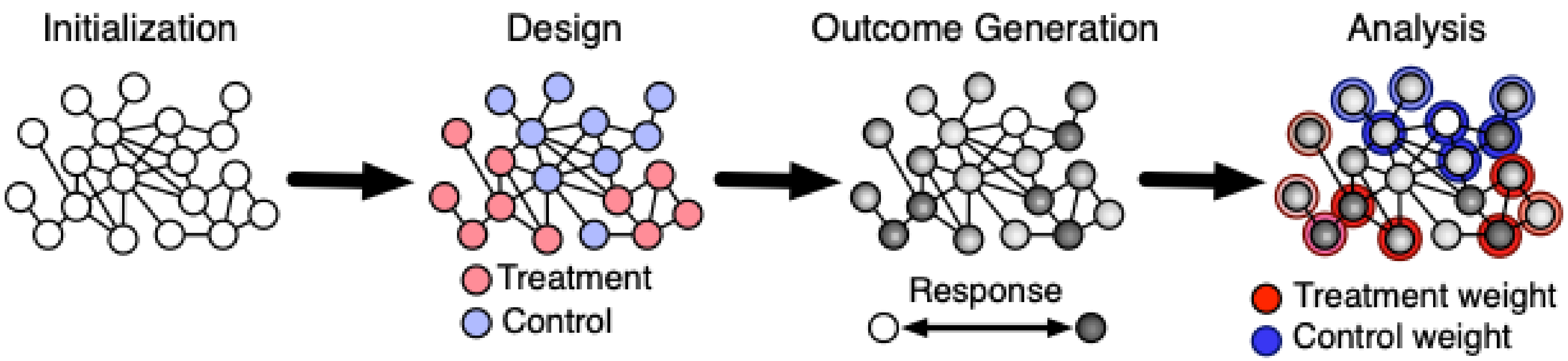


Image credit: Johan Ugander, Stanford

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

Network Experimentation summary

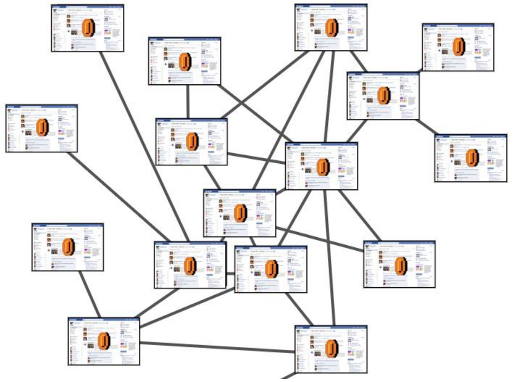


- Initialization: An empirical graph or graph model
- Design: Graph cluster randomization
- Outcome generation: Observe behavior (or observe model)
- Analysis: Discerning effective treatment

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!

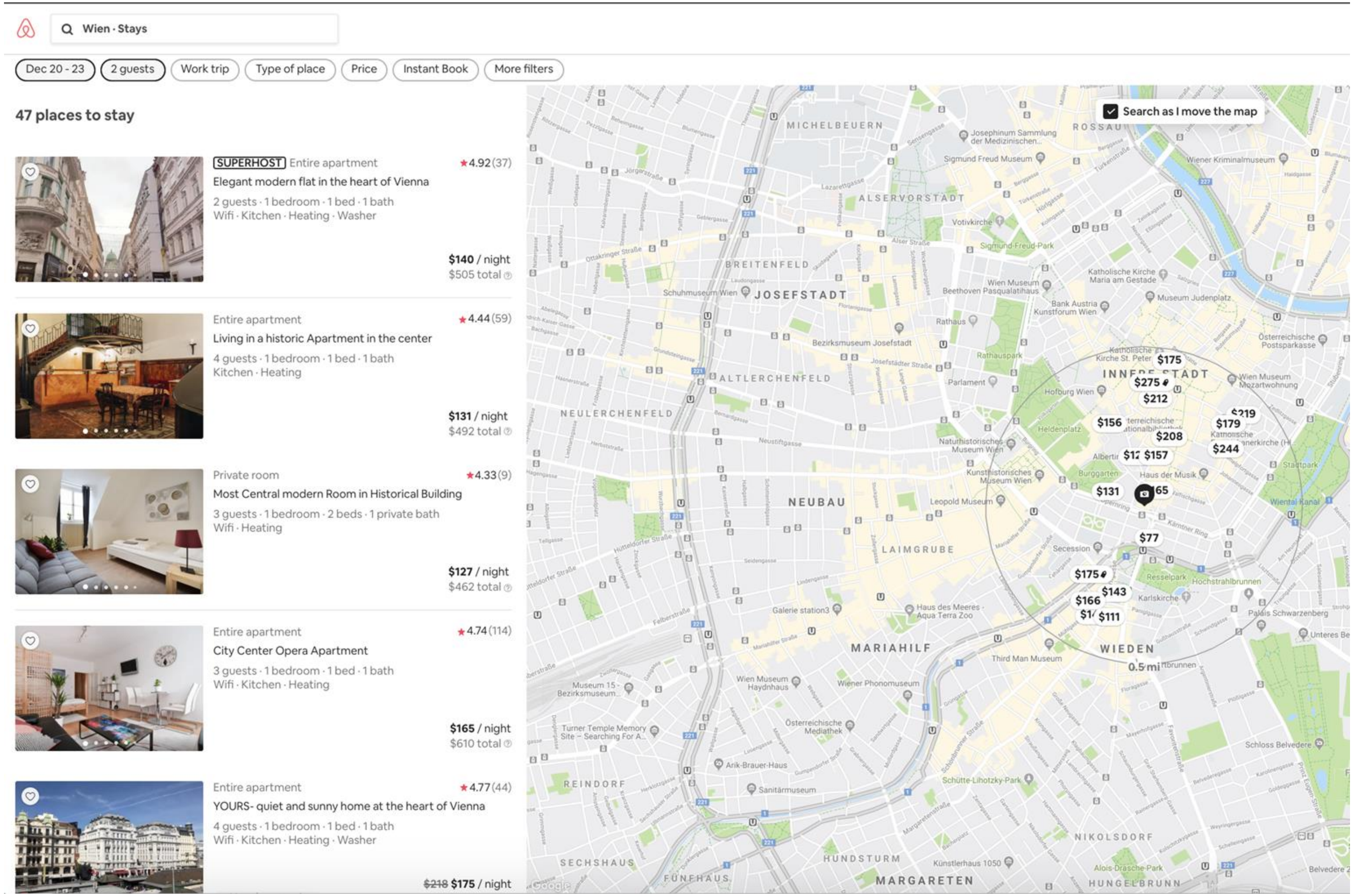


Interference in marketplaces

- 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

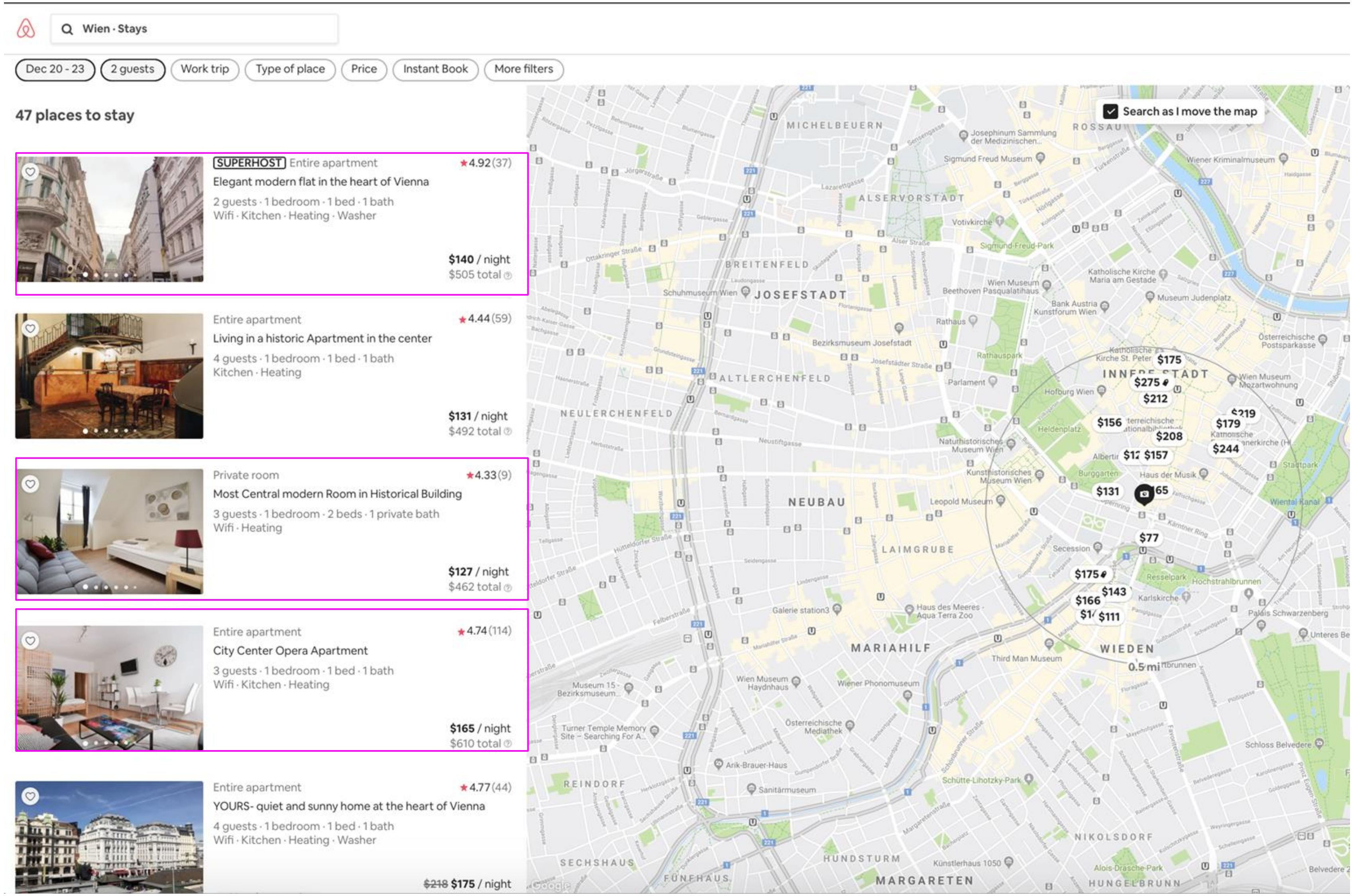
  Cannibalization effect would not occur; only attraction of new customers
- Tonight and next time: experimentation in marketplaces under interference

Example: price change experiment on Airbnb



Slide credit:
Dave Holtz,
UC Berkeley

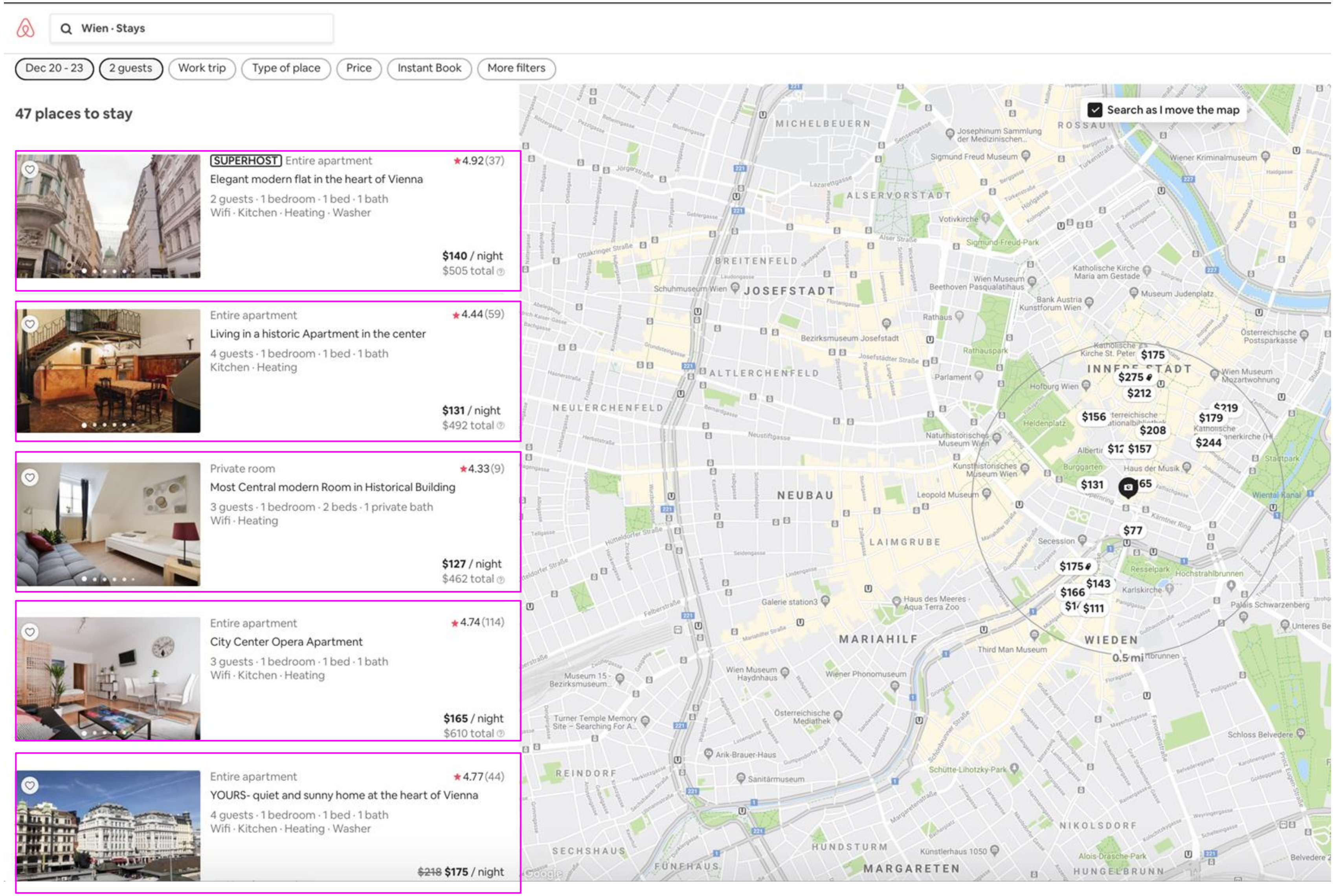
Example: price change experiment on Airbnb



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

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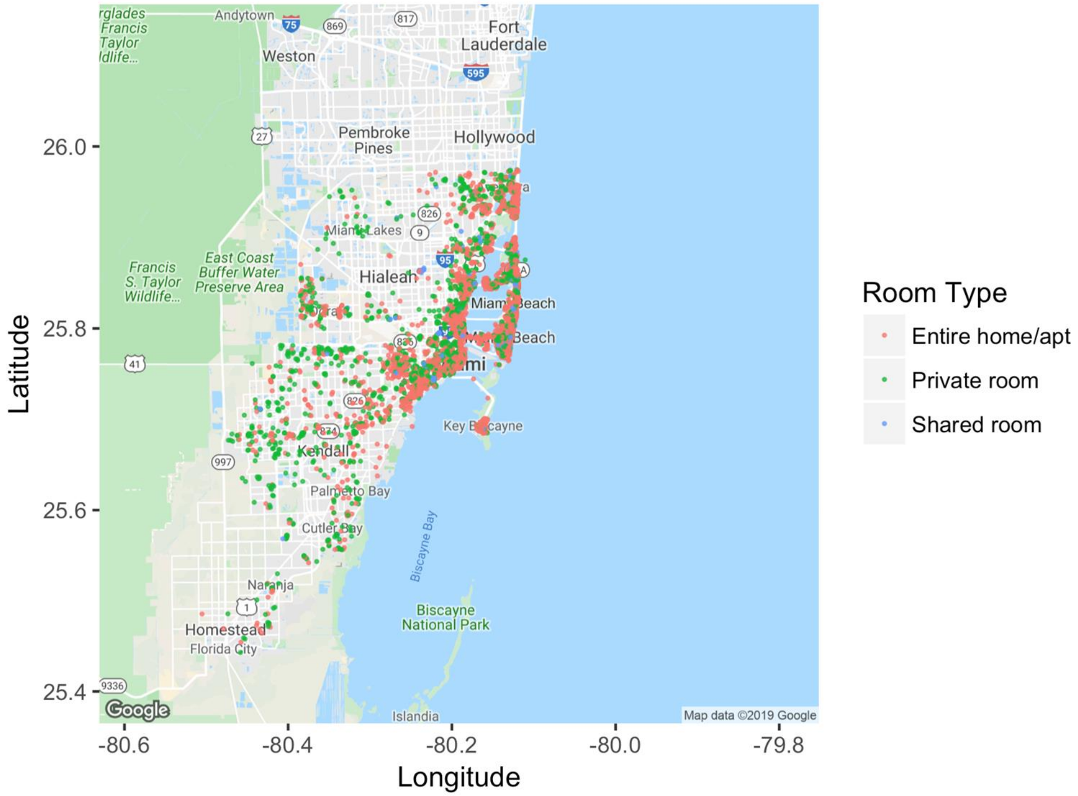
Approach 1: transform the marketplace into a network



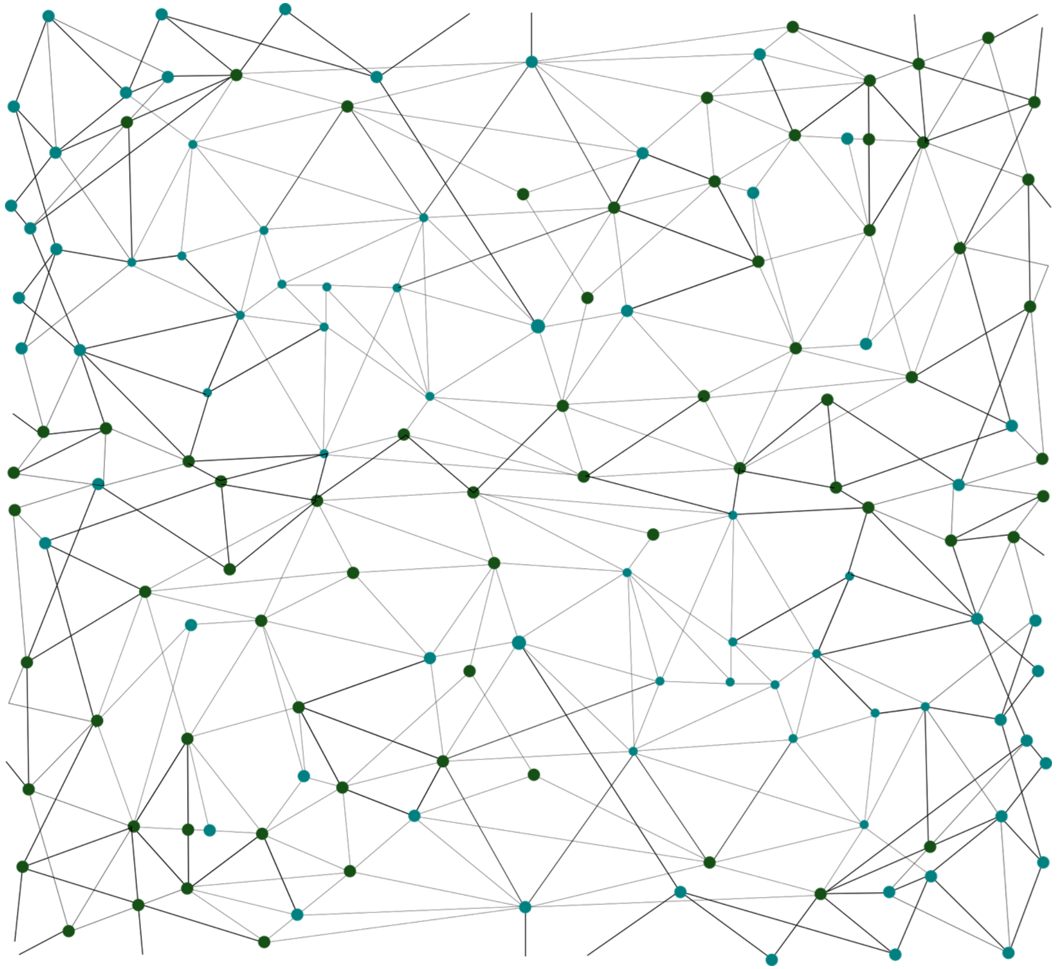


Image source

Network experiment designs + analysis techniques

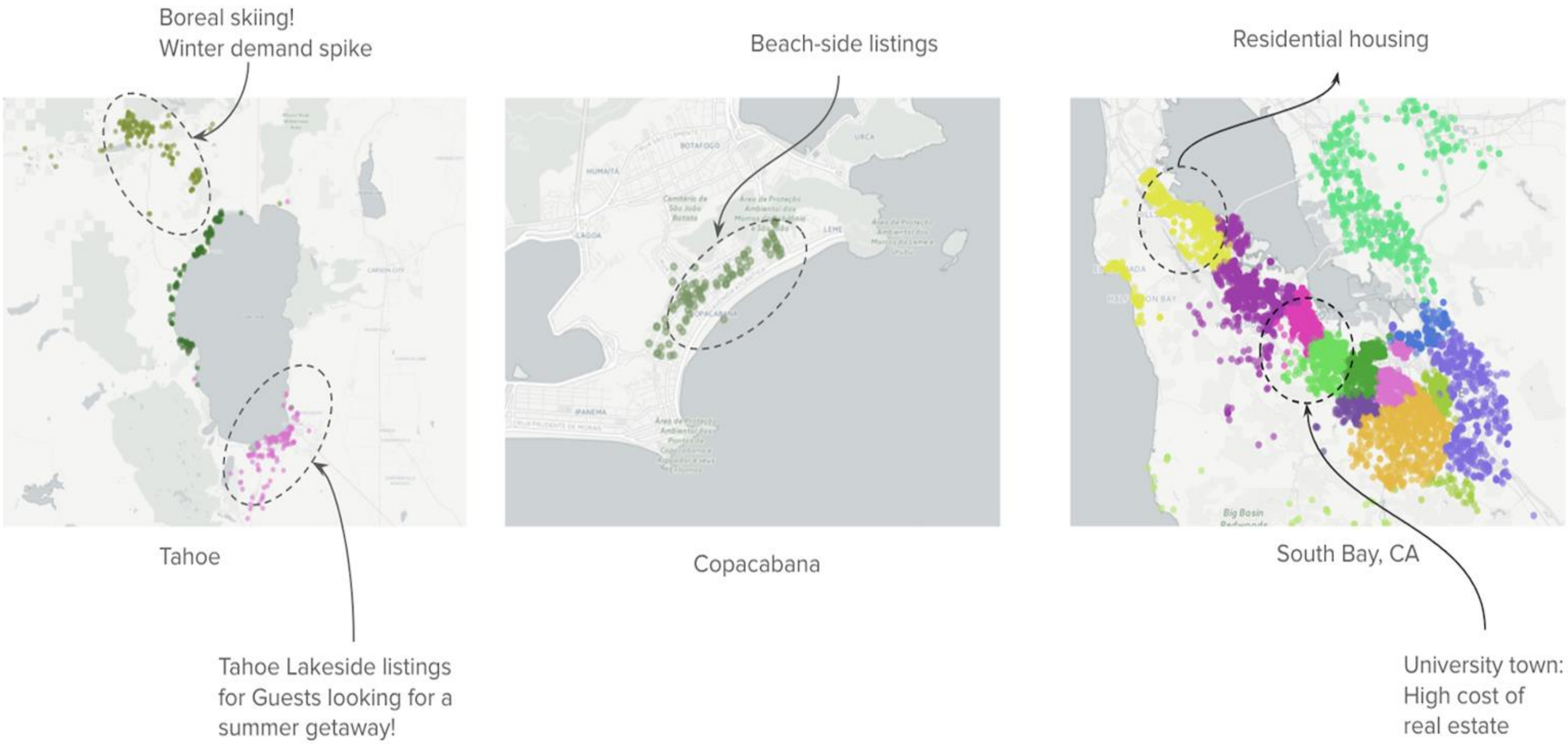
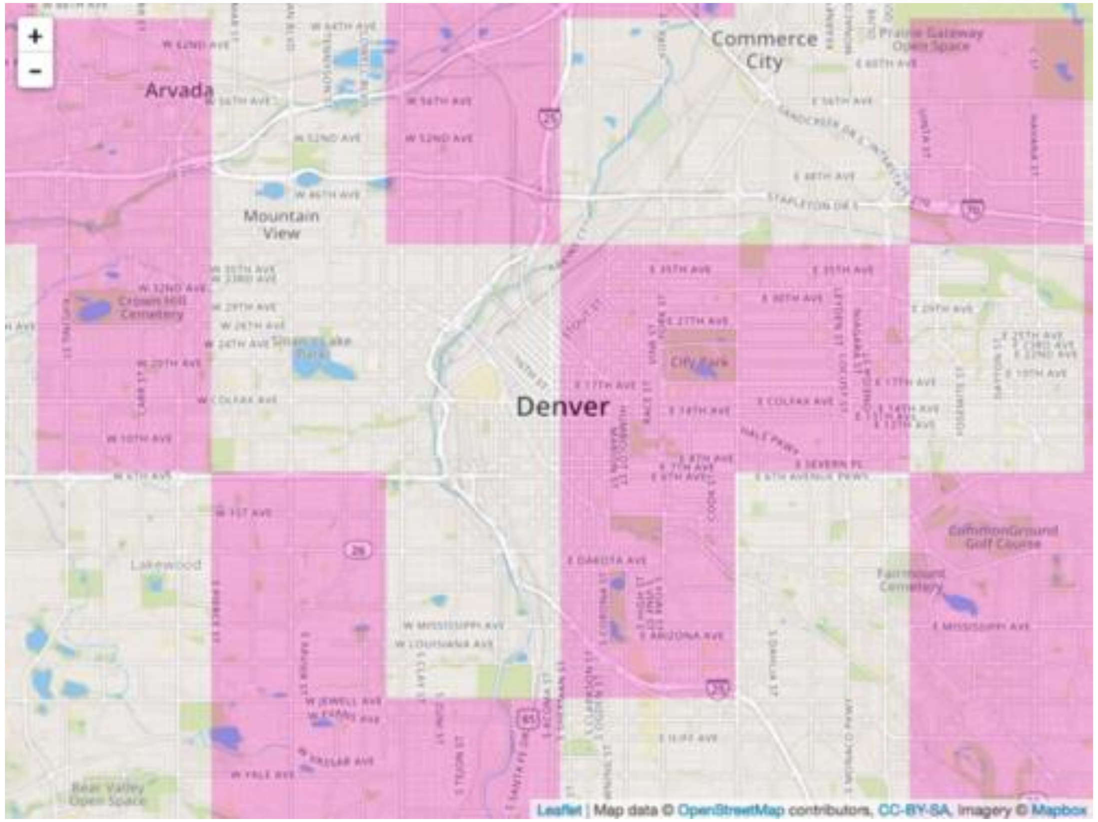
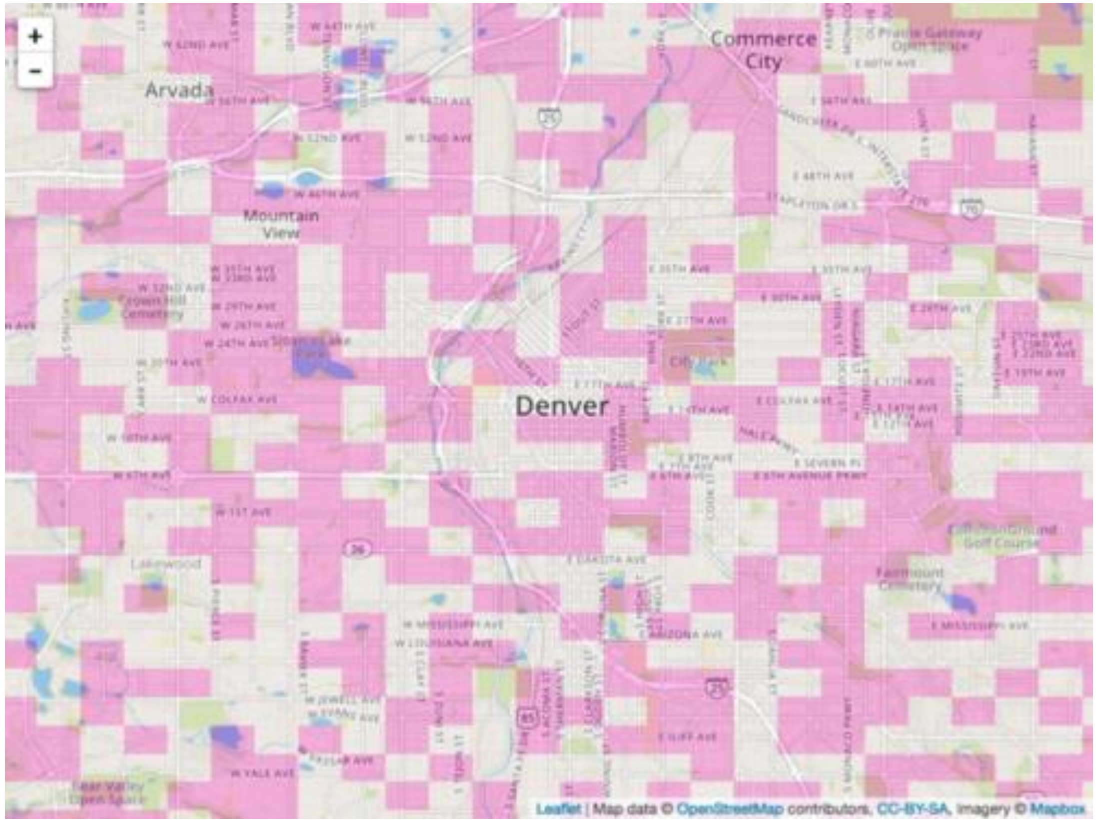


Image credit: Dave Holtz, UC Berkeley

- 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

Spatial randomization in ride-hailing





[Experimentation in a Ridesharing Marketplace | by Nicholas Chamandy | Lyft Engineering]

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