Incrementality at Netflix

ARF Incrementality Summit

Randall Lewis
January 24, 2019

NETFLIX

Abstract

Measurement of advertising effectiveness is essential to improve marketing strategies and tactics. Incrementality is the causal measurement of advertising effectiveness, achieved through experimental and modeled approaches. Placing advertising effectiveness within the rich literature of causal inference, Netflix uses incrementality to improve and optimize advertising decision making. This talk will provide a general overview to incrementality thinking, with detailed examples of applications.

Main Contributors

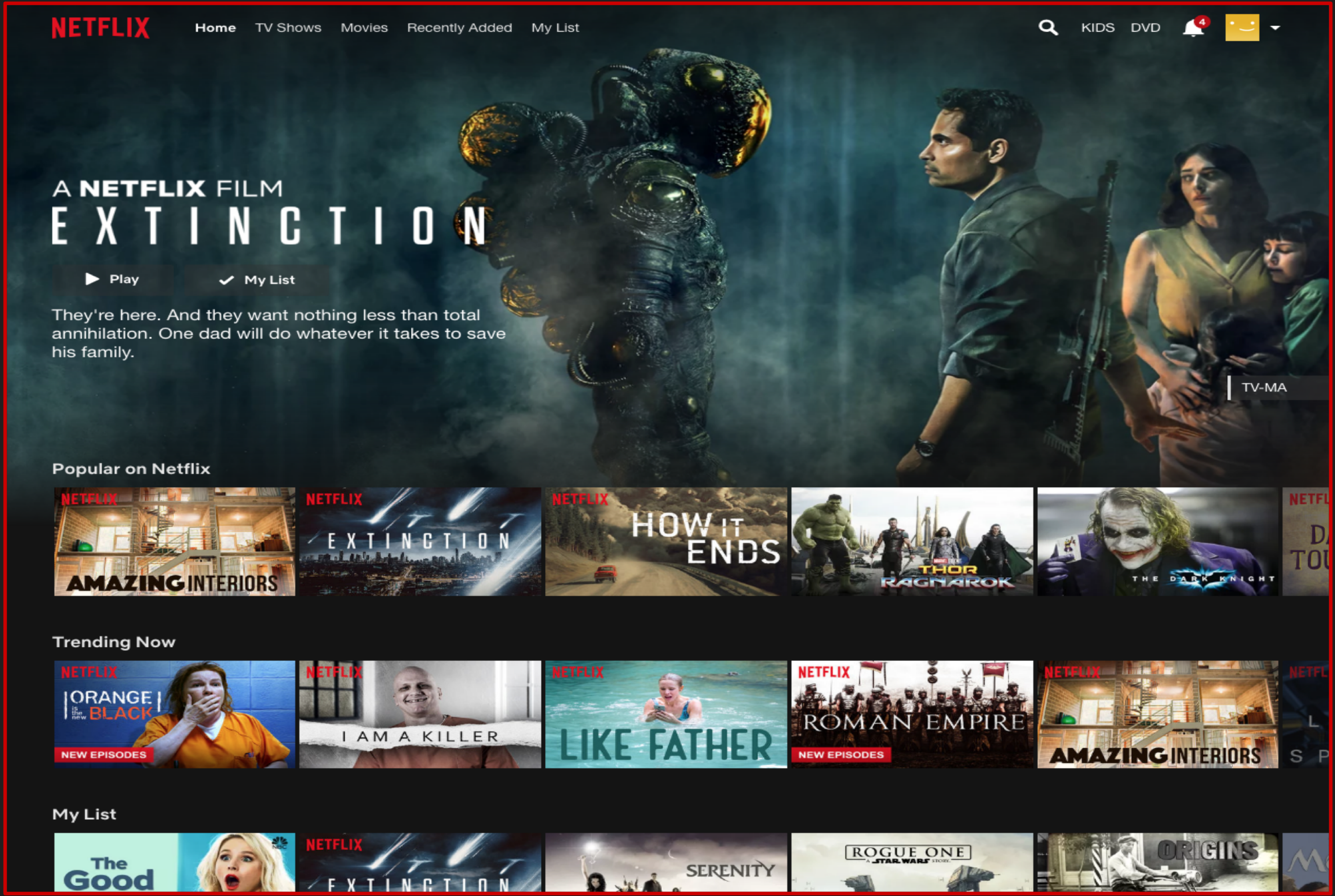
My Netflix hat tip

- Jeffrey Wong
- Benoit Rostykus
- Steve McBride
- Julia Glick
- Vijay Bharadwaj
- **Many** other stunning colleagues.

Bio: Randall Lewis

Randall Lewis is the Director of Economics on the Science & Algorithms team at Netflix. He designs and builds causal measurement and prediction systems to guide business decision-making. He has developed advanced techniques to measure the causal impact of advertising, create advanced AB-testing platform analytics, and measure the value of entertainment media in order to help both humans and automated decision systems make better choices. Before joining Netflix he worked at Google and Yahoo. Randall attended MIT as a Presidential Fellow where he earned his PhD in economics.

“Marketing” at Netflix


NETFLIX
Home
TV Shows
Movies
Recently Added
My List
KIDS
DVD
4
A NETFLIX FILM
EXTINCTION
Play
My List
They're here. And they want nothing less than total annihilation. One dad will do whatever it takes to save his family.
TV-MA
Popular on Netflix
AMAZING INTERIORS
EXTINCTION
HOW IT ENDS
THOR RAGNAROK
THE DARK KNIGHT
Trending Now
ORANGE is the new BLACK
NEW EPISODES
I AM A KILLER
LIKE FATHER
ROMAN EMPIRE
NEW EPISODES
AMAZING INTERIORS
My List
The Good
EXTINCTION
SERENITY
ROGUE ONE
A STAR WARS STORY
ORIGINS

Marketing Channels

- Internal Marketing
  - In-product ranking and promotional canvases
- External Marketing (focus of talk)
  - Paid, owned, and earned promotion
  - 2018 Budget ~$2B (CNBC)

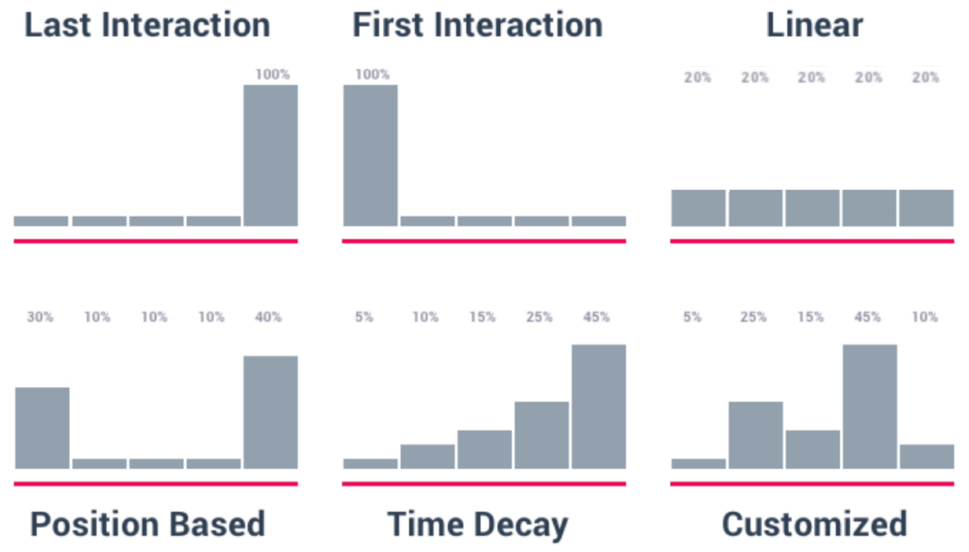
“Incrementality” and Advertising Effectiveness

Netflix Marketing Objective

"Get people so excited about our **content** that they **sign up** and watch"

- **Science goal**: measure and optimize advertising effectiveness to support growth objective

Measuring Advertising Effectiveness



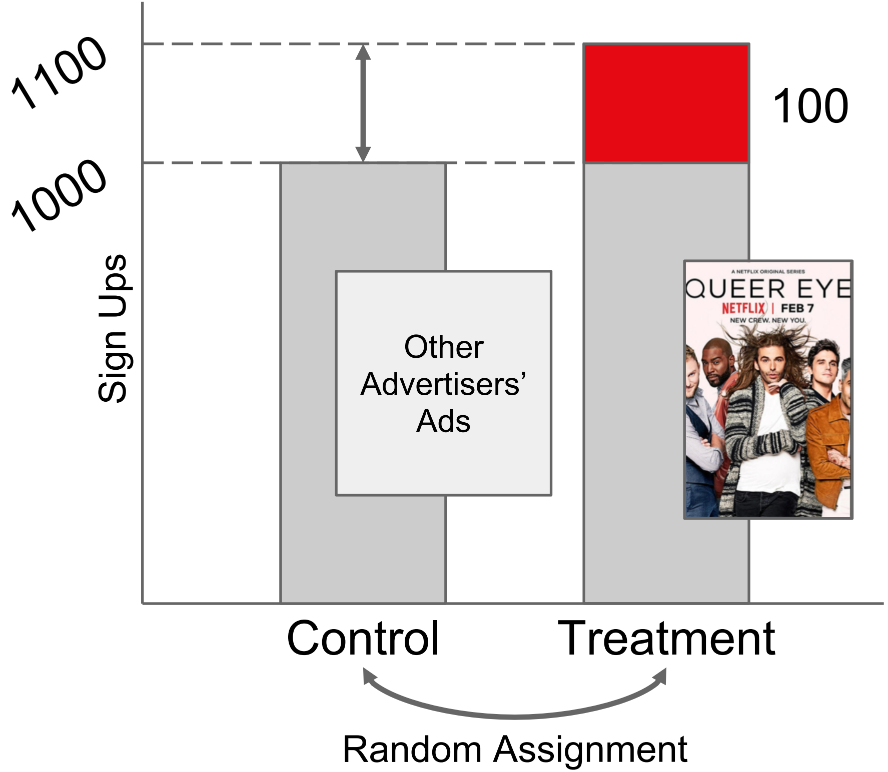
Measure the effects of the advertising

Success Metric (Reward): Sign Ups

Attribution: assign credit (apportion the reward) to the actions that preceded the success

Conceptual: Not all success events (sign ups) are *caused* by the action.

Incrementality: the *Causal* effect of an Ad



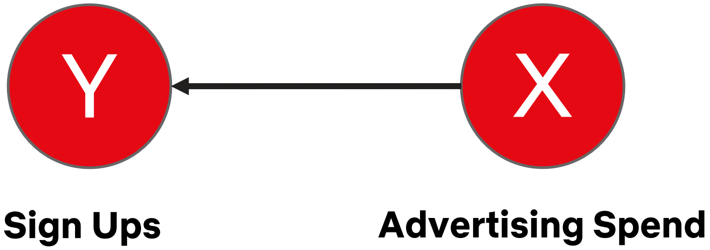
Incrementality: Measuring ad effects based on the difference in the outcome ***because*** the ad was shown

Requires a comparison group (to represent the **counterfactual**)

Johnson, Garrett A. and Lewis, Randall A. and Nubbemeyer, Elmar I, Ghost Ads: Improving the Economics of Measuring Online Ad Effectiveness (January 12, 2017). Simon Business School Working Paper No. FR 15-21. Available at SSRN: https://ssrn.com/abstract=2620078

Causal Inference

Ads (and ad spend) cause sign ups



Model

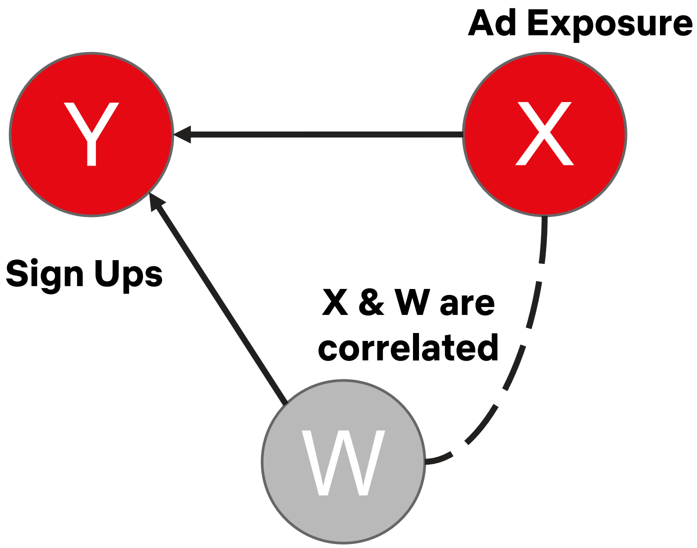
$E(Y|X) = \alpha + \beta X$

Inference

β: More sign ups when advertising spend is greater

Reality: Other factors matter so **valid** measurement impossible (including advertising because there are sign ups = Xmas)

Why not compare *Exposed* to *Unexposed*?



Model

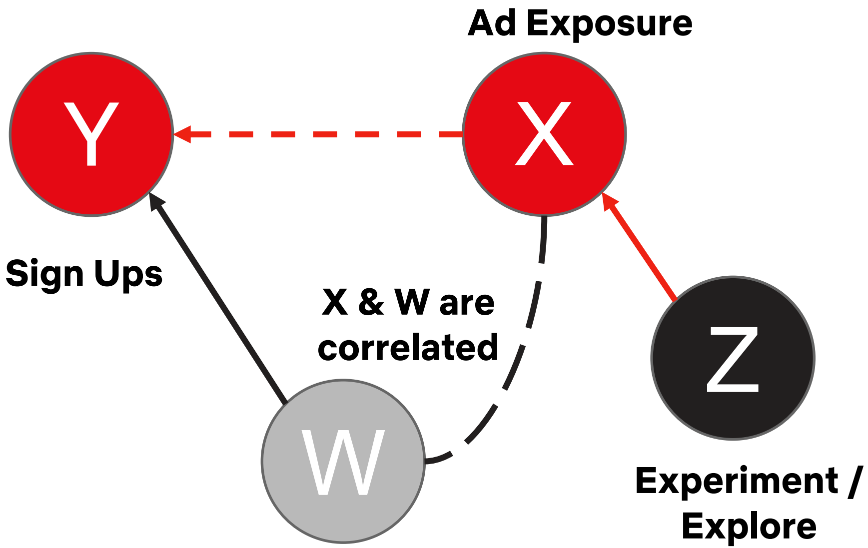
$$E(Y|X) = \alpha + \beta X + \omega W$$

Inference

β: More sign ups among ad **exposed** (controlling for other things)

Reality: Ad servers depend on features (W) that directly increase sign up rates. That is, they show ads to higher intent people, so can't (directly) evaluate the ad effect

“This is how the world works” (locally)



Model

$E(Y|X) = \alpha + \beta P_z X + \omega W$

Inference

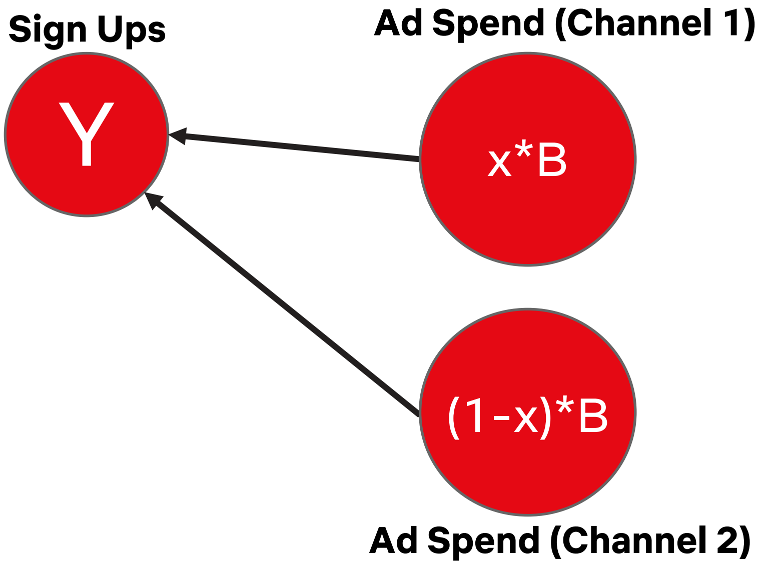
β: more sign ups cased by ad exposure *among those who get exposed as intended*

Reality: when you control the **DGP**, you obtain valid inference for treatment effects (from ads, or otherwise)

Applications

- Channel Mix
- Title (product / creative) selection for ads
- Incrementality Bidding

Application: Channel mix / Budget share



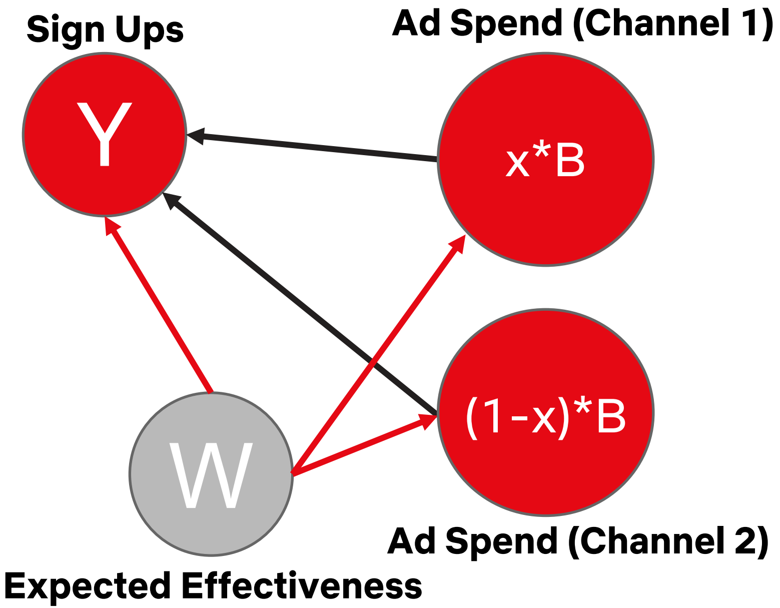
Model

$E(Y|X) = \alpha + \beta_1 x^*B + \beta_2(1-x)^*B$

Inference

$\boldsymbol{\beta}_K$: more sign ups from spend (B) in channel *K*

Problem: spend depends on expected effectiveness



Model

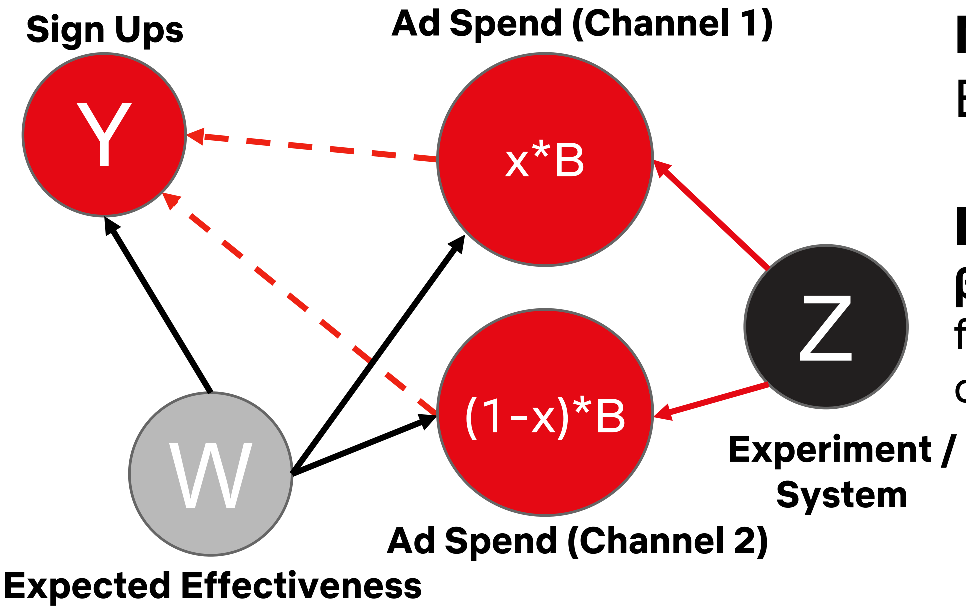
$E(Y|X) = \alpha + \beta_1 x^*B + \beta_2(1-x)^*B + \omega W$

Inference

$\boldsymbol{\beta}_K$: more sign ups from spend (B) in channel K

Reality: allocating advertising based on expected effectiveness invalidates standard 'MMM' approaches to ad effect inference

Solution: vary channel mix (experiment / system)



Model

$$E(Y|X) = \alpha + \beta_1 P_z x^*B + \beta_2 P_z (1-x)^*B$$

Inference

$\boldsymbol{\beta}_K$: more sign ups from spend (B) in channel K for the budget added / removed from that channel

Reality: Only by ignoring expected effectiveness when allocating, can channel effectiveness be evaluated (locally)

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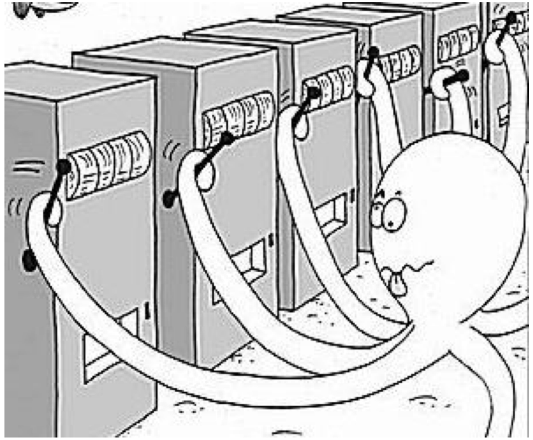
Application: Explore-Exploit for title selection



Which title is **most incremental** this week?

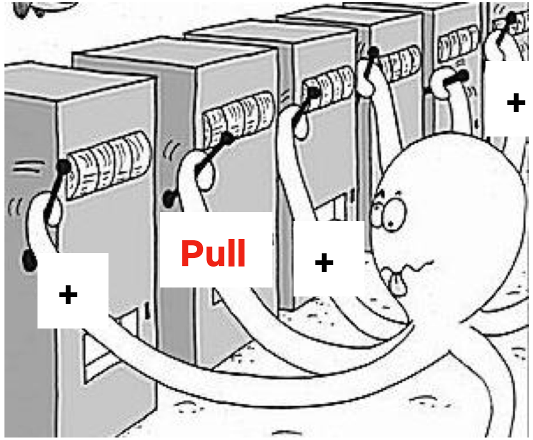
vs.

vs.

Bandit Approach: explore among titles, and converge on most effective title (exploit)

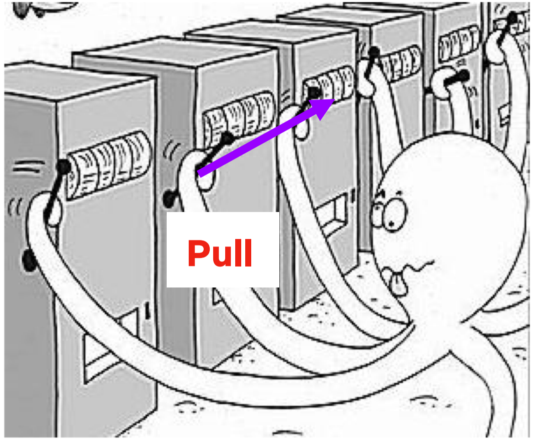
1. Assumes fixed reward (stationarity)
2. (Generally) assumes zero return from inaction

Problem: … troubles at the casino



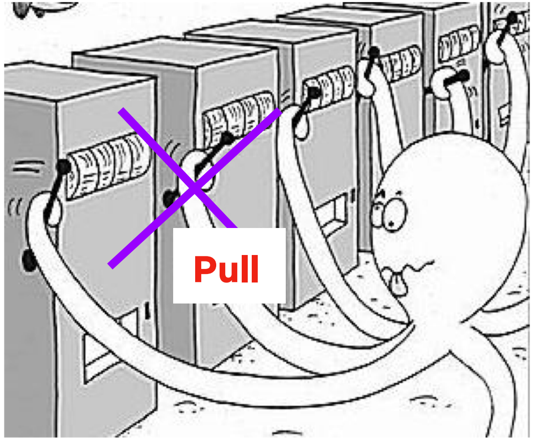
Organic Bid Modifiers

(change in reward for other arms)



Combined machine

(reward from other arm)



Auction-related non-compliance

(no reward)

Reality: ad systems often generate biased training data, hampering optimization for incrementality

Application: Incrementality Bidding

Ad Effect $$\overbrace{P(signup|W,U,X=1)}^{\textbf{Ad}} - \overbrace{P(signup|W,U,X=0)}^{\textbf{No Ad}}$$

- Confounded (biased) data
  - *Selection on the Outcome* (Negative targeting)
  - *Non-compliance*
  - *Activity Bias* (temporal variation not causal)
- Insufficient Auction Logging: counterfactual (opportunity) logging often insufficient to overcome biased ad exposure
- **Data Scale** and system architecture

Solution: innovate in methods and systems arch.

Incrementality Bidding & Attribution[1]

By Randall Lewis, Netflix
Jeffrey Wong, Netflix

First Draft: 2017/04/21
This Draft: 2018/03/08

- **Causal Bandits** (engineered instruments to obtain unconfoundedness)
- **Downsampling** (data scale management)
- **Continuous-time modeling** (gain from assumed response shape)
- **Causal correction** (use larger, but biased correlational data)

Available at ssrn.com/abstract=3129350

Key Takeaway:

“Incrementality” improves decision-making in many business applications where human judgment or machine learning confound measurement: correlation ≠ causation.