An Industry Perspective on A/B Testing

Huizhi (Kenny) Xie

2024.03.09

CONTENTS

/01 Why A/B Testing?

Let's Start With The Growth Logic Of An Internet Company.

- An internet company builds product/service for its users.
- The product/service has its own value proposition.
- Users use the product/service and provide feedback.
- The internet company improves its product/service based on users' feedback for continuous growth.

User's Feedback Is Important Because It Is Not Easy To Come Up With Ideas That Work.

Microsoft

At Microsoft, 1/3 of the ideas improved business metrics, 1/3 had no impact on business metrics, 1/3 degraded business metrics.

- Kohavi 2009

Google

In well-optimized search engine, only 10%-20% of ideas improved business metrics.

- Jim Manzi 2012

Slack

70% of our ideas were abandoned.

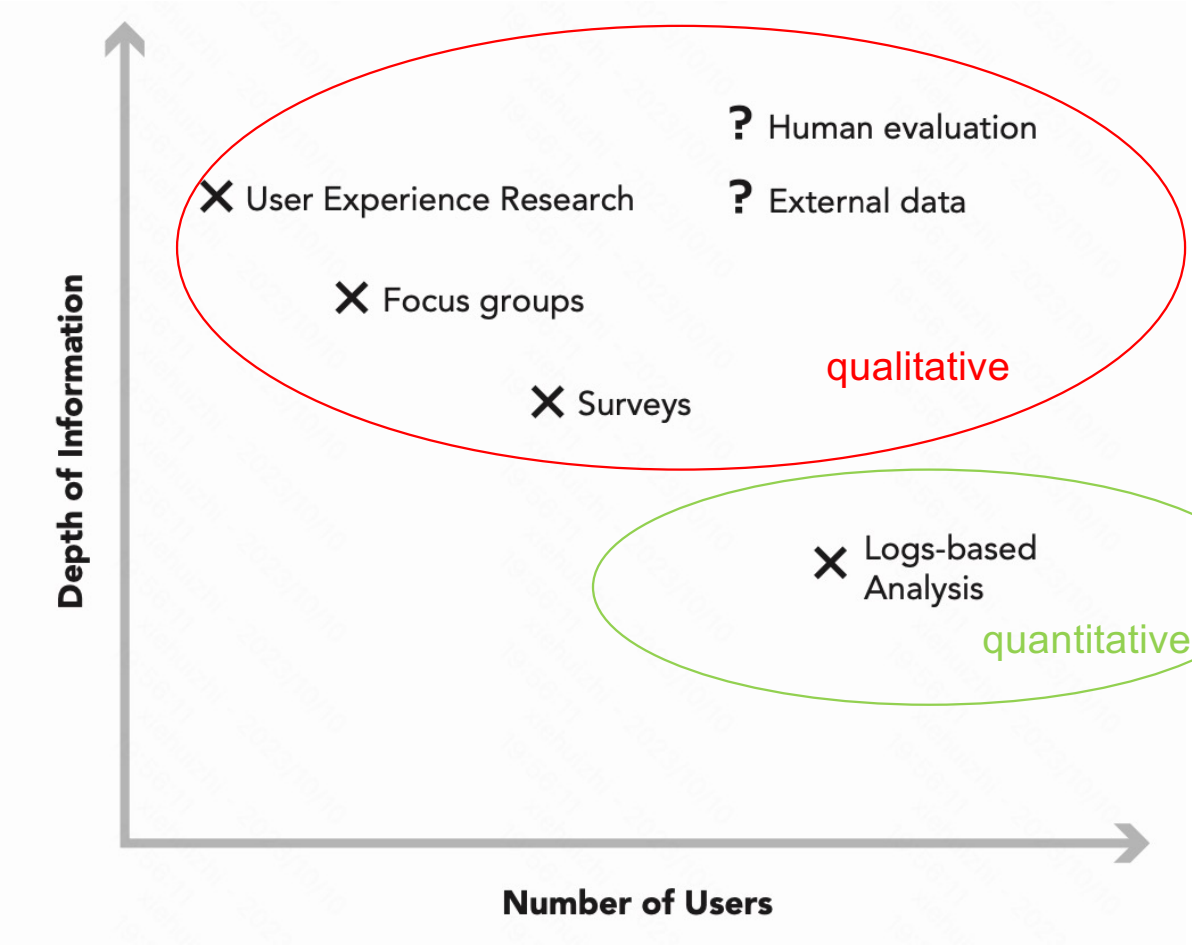
- Mosavat 2019

Netflix

90% of our ideas were wrong.

- Mike Moran 2007

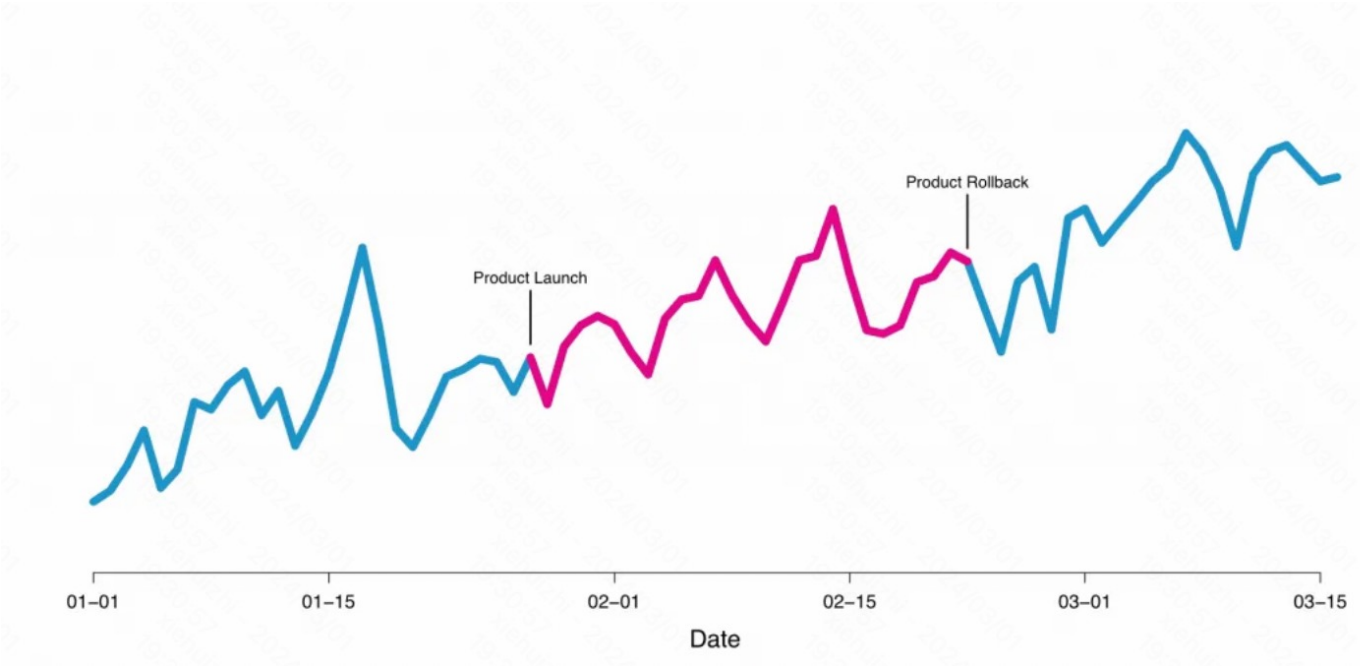
User's Feedback Can Be Qualitative Or Quantitative.



Data-driven Product Development Based On Quantitative Feedback Is The Buzzword These Days.

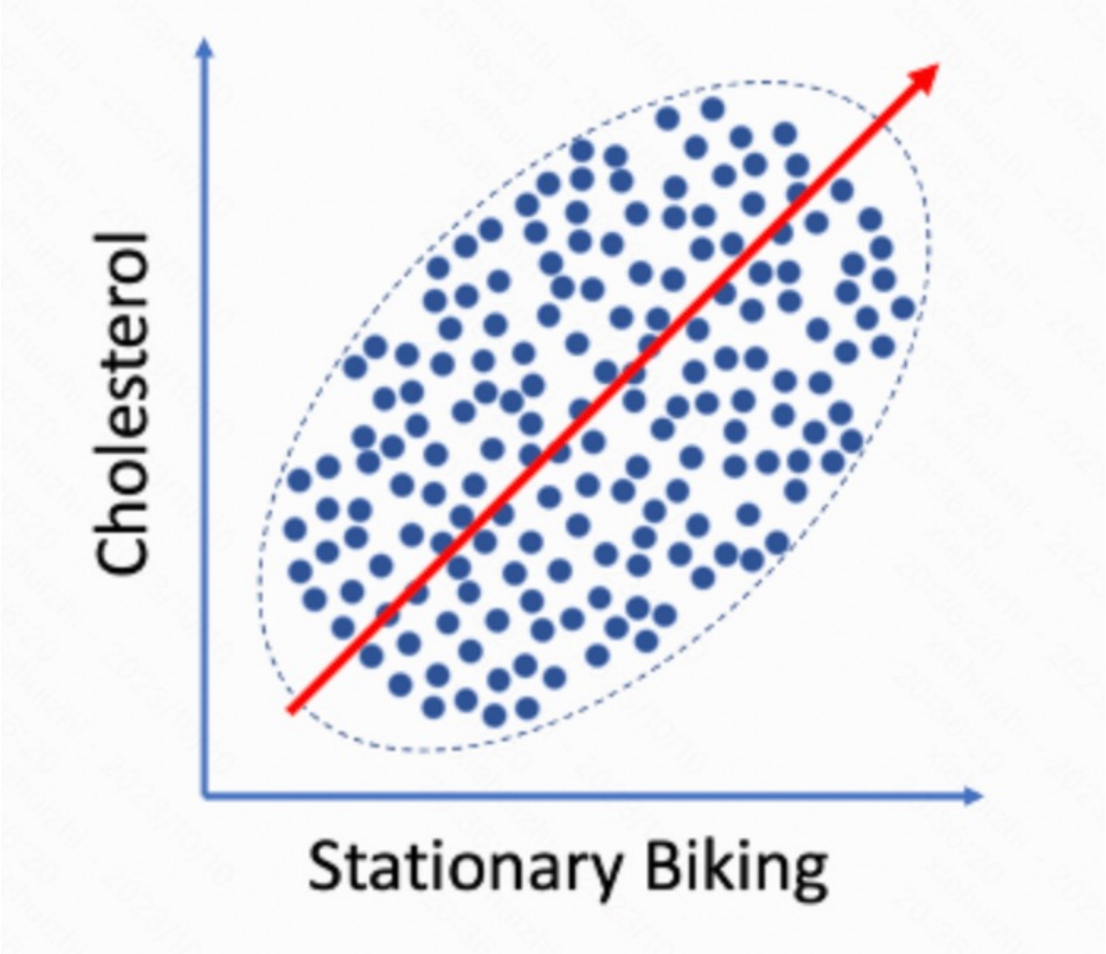
- Data-driven product development is more efficient.
- For data-driven product development to work, there are two key elements:
  - Metric: measure value delivered to users
  - Causal inference: link what a company does to improvement in the metric, or incremental value delivered to users

Causal Inference Is Not Easy: An Airbnb Example

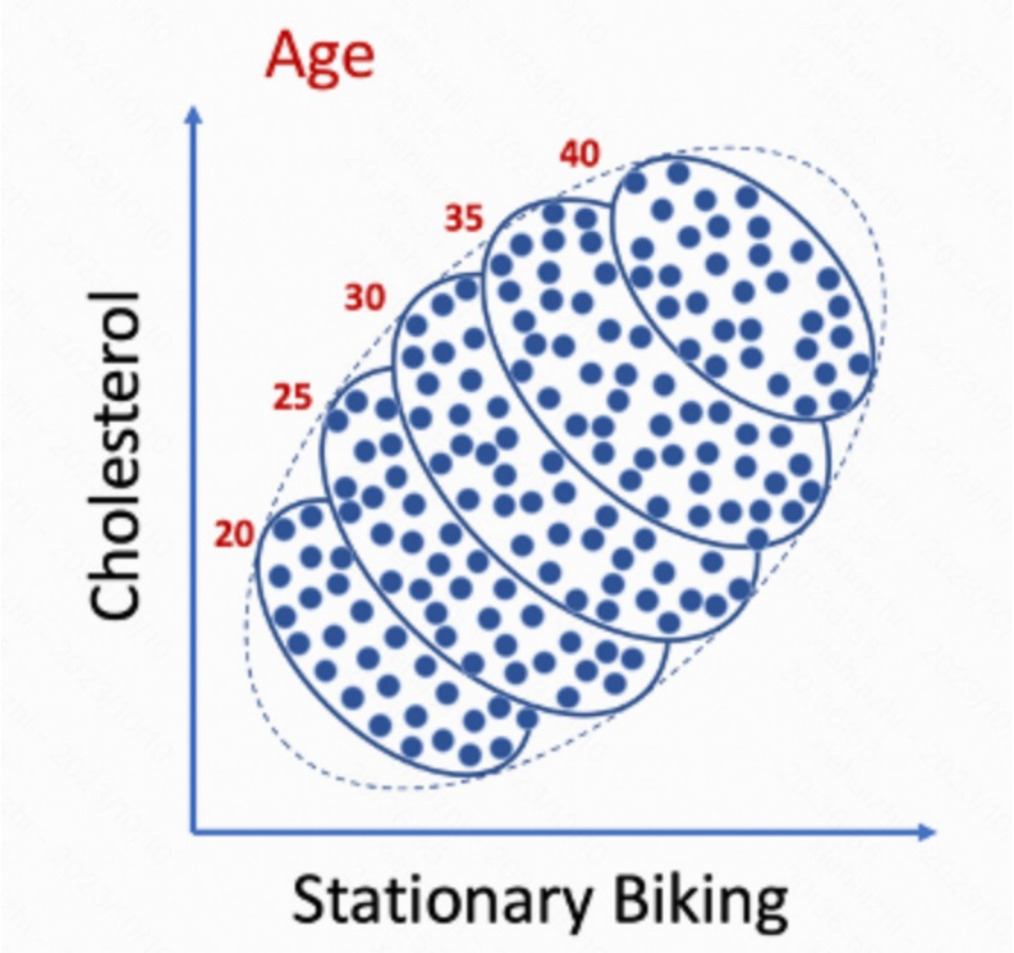


https://medium.com/airbnb-engineering/experiments-at-airbnb-e2db3abf39e7#.miqyczkzb

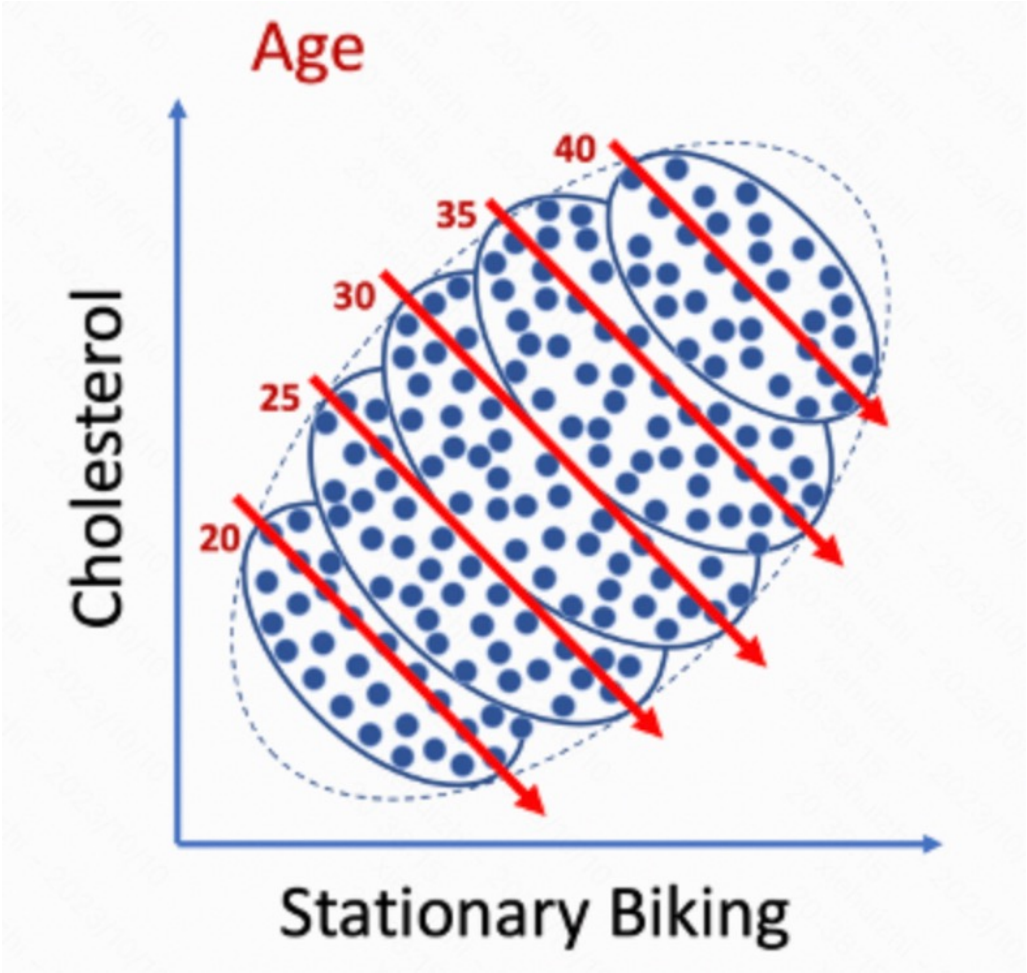
Causal Inference Is Not Easy: A Real Life Example



Causal Inference Is Not Easy: A Real Life Example



Causal Inference Is Not Easy: A Real Life Example

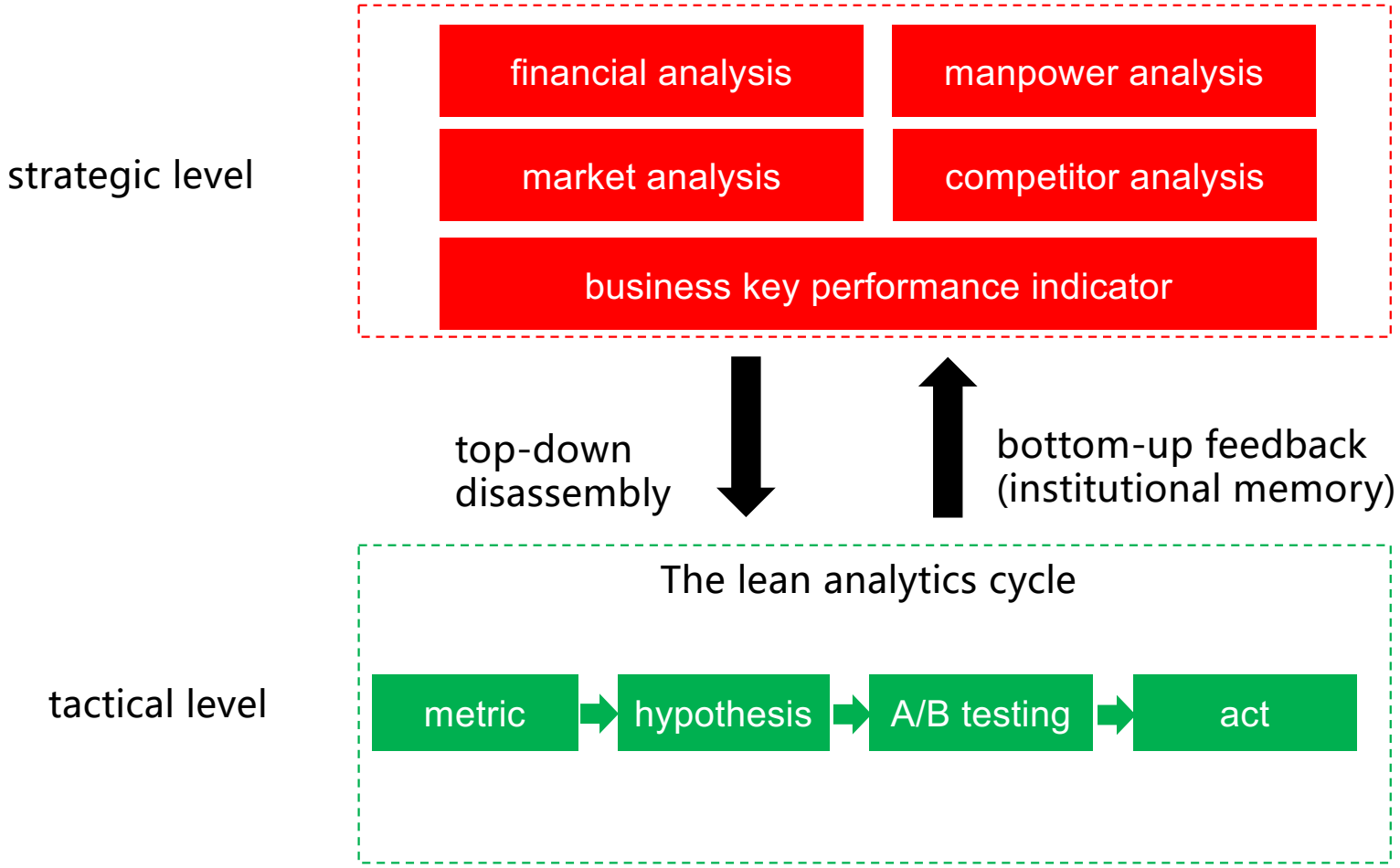


A/B Testing Is The Gold Standard For Causal Inference.

An A/B Testing Pyramid

Courtesy of Brooks Bell

A High-level View Of An Internet Company's Data-driven Operation

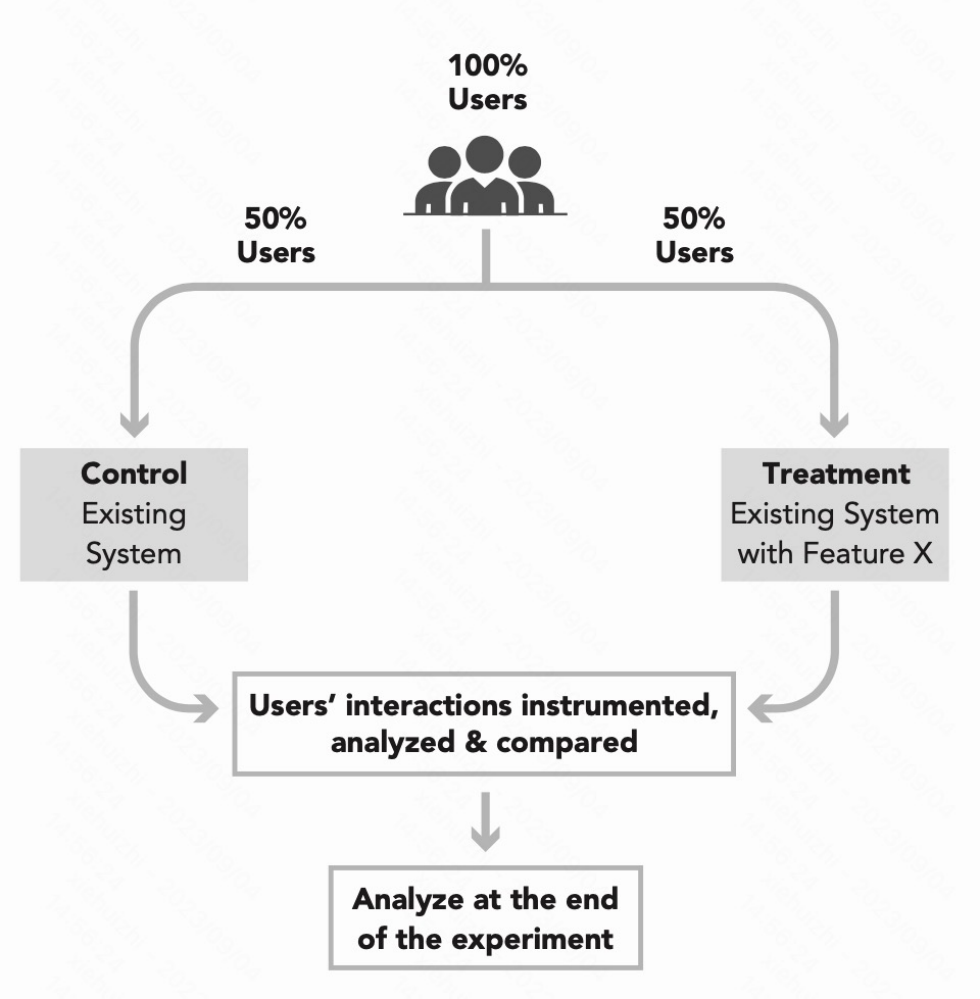


Internet Company Tests Almost Everything Online.

- Relevance algorithms (search, ads, personalization, recommendation, and so on)
- User interface (UI)
- Latency/performance
- Content management systems
- Customer support systems
- Backend code changes
- …

/02 What is A/B Testing?

A/B Testing In One Slide (Kohavi, Tang and Xu 2020)



Online Experiment Is A Unique Type of Experiment: Same Science, Different Application

- Large traffic volume
- Low cost of data collection
- Lots of evaluation criteria
- Relatively small treatment effect
- Concurrent experiments on the same user set
- …

Statistical Inference For A/B Testing In One Slide

A pair of hypotheses:

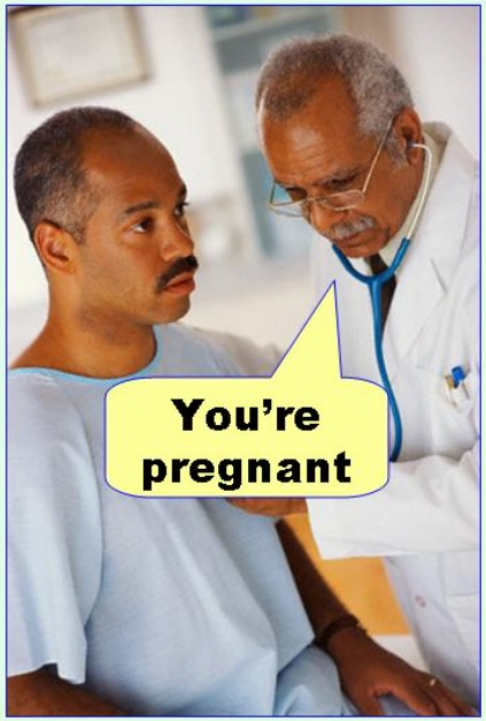
$$H_0 : \mu_A = \mu_B \quad \text{VS} \quad H_1 : \mu_A \neq \mu_B$$

Two types of error:

	H0 is true	H1 is true
reject H0	Type I error	correct decision
reject H1	correct decision	Type II error

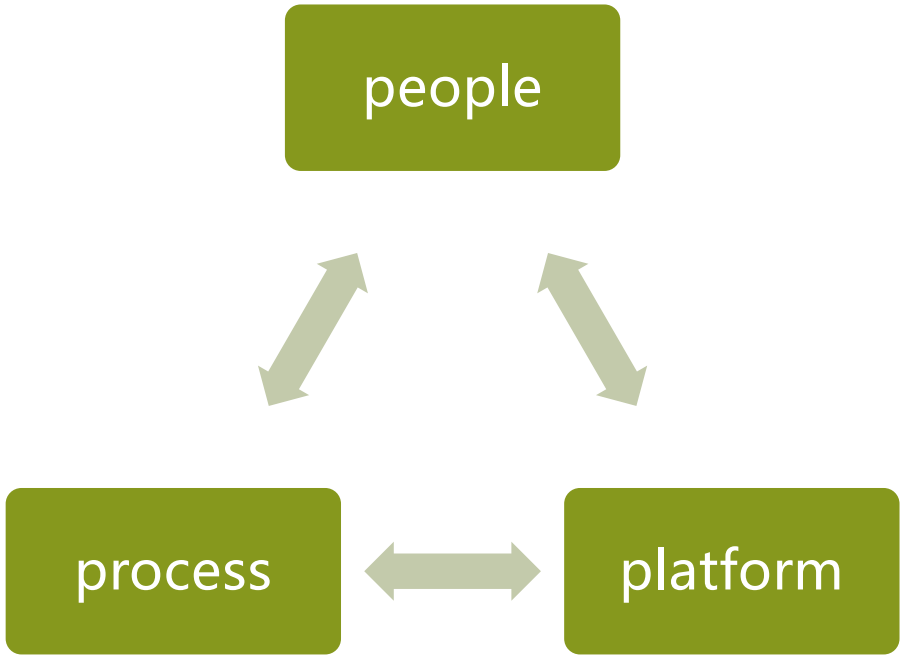
Understanding The Two Types of Error: Analogy To Pregnancy Test

Type I error
(false positive)



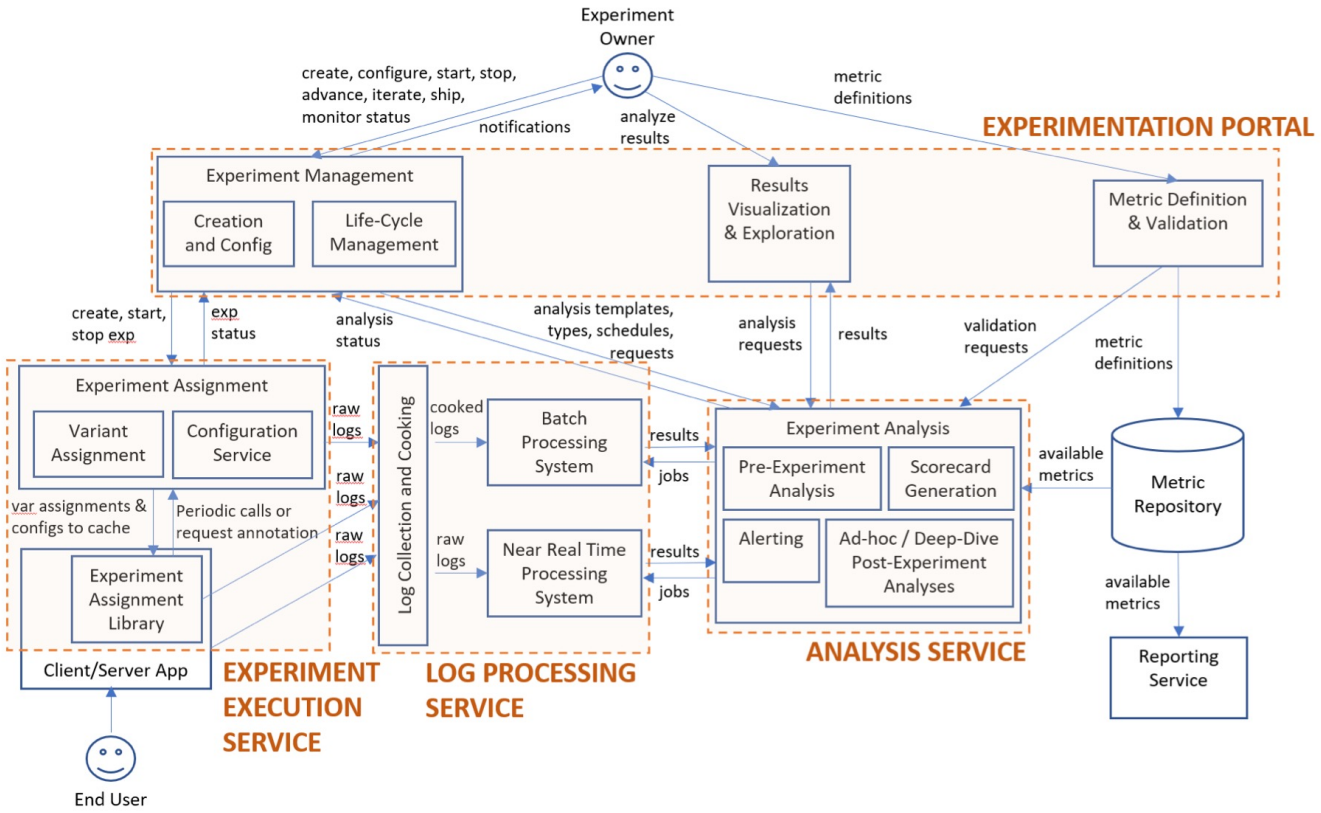
Type II error
(false negative)

Internet Company's A/B Testing Ecosystem



https://engineering.linkedin.com/ab-testing/why-experimentation-so-important-linkedin

Architecture Of A Large-scale Online Experiment Platform (Gupta et al. 2018)



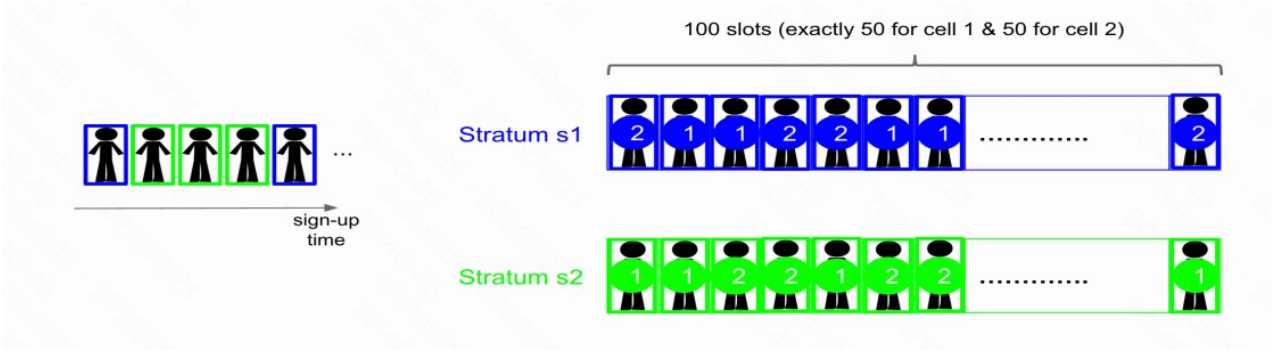
/03 Top Practical Challenges

Improving The Sensitivity Of Experiments: Problem

- Recall the two types of errors in frequentist statistical inference
- Two types of error conflict with each other. With type I error controlled at a nominal value, sample size, true delta, and sampling variance of a metric affect type II error.
- Reducing type II error is to improve the sensitivity of experiments.
- Sampling/randomization or analysis stage to reduce type II error?

Netflix's Real Time Stratified Sampling System (Xie & Aurisset 2016)

(a)	1	2	3	4	5	6	.	.	.	.	.	.	.	100
(b)	25	57	9	12	95	64	.	.	.	.	.	.	.	43
(c)	1	2	1	1	2	2	.	.	.	.	.	.	.	1



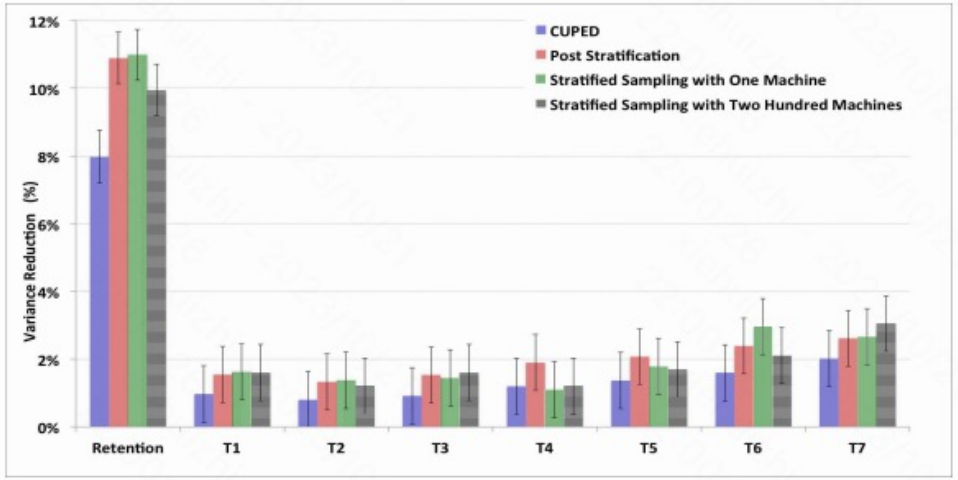
Stratified Sampling, Post Stratification And CUPED Are Asymptotically Equivalent. (Xie & Aurisset 2016)

- $\bar{Y}$: simple average
- $\widehat{Y_{strat}}$: weighted average based on strata proportion
- $Var_{srs}(\bar{Y})$: variance of simple average under simple random sampling
- $Var_{strat}(\bar{Y})$: variance of simple average under stratified sampling
- $Var_{srs}\left(\widehat{Y_{strat}}\right)$: variance of weighted average under simple random sampling
- $Var_{strat}\left(\widehat{Y_{strat}}\right)$: variance of weighted average under stratified sampling
- n : sample size

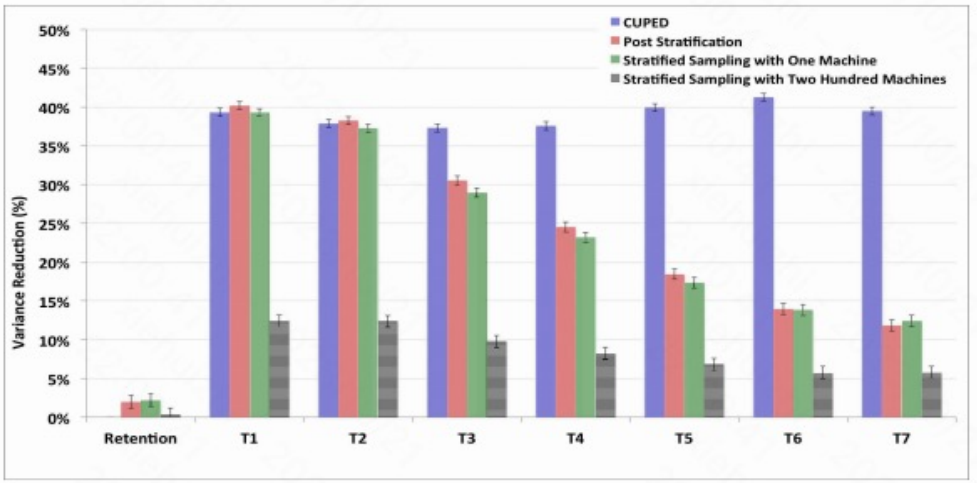
- It can be shown:

$$var_{strat}(\hat{Y}_{strat}) = var_{srs}(\hat{Y}_{strat}) + O(\frac{1}{n^2}) = var_{srs}(\bar{Y}) + O(\frac{1}{n}),$$
$$var_{strat}(\hat{Y}_{strat}) \leq var_{srs}(\hat{Y}_{strat}) \leq var_{srs}(\bar{Y}).$$

Numerical Results Based On Real Experiment Data (Xie & Aurisset 2016)



new users



old users

Estimating The Long-term Effect: **Problem**

- The impact of a change may take a long time to materialize in terms of key product metrics.
  - Impact of change of ranking results in an online travel service materialize after customers stay in a vacation rental or hotel room months after booking
  - Increasing number of ads in search results bring in more revenue at first but might have the opposite effect due to user attrition
  - Introduction of clickbaits on a content provider service may cause increase in clicks due to novelty effect but may induce larger dissatisfaction in the long term

Estimating The Long-term Effect: Common Solutions and Challenges

- Long-term experiments or holdouts
- Proxies
- User learning modelling
- Surrogates

A Short Discussion On Long-term Experiments Or Holdouts

- Software development cycle is usually short.
- Engineering cost to maintain a code fork that is not updated for a long time
- Non-persistent user tracking and network interactions
- The above said, it is worth learning novelty effect or primacy effect.

A Short Discussion On Proxies

- Head company's approaches:
  - Netflix used logistic regression and survival analysis to find good predictors of user retention.
  - LinkedIn created metrics based on lifetime value model.
  - Uber found some macro-economic models to be useful in finding good proxies.
  - Bing and Google have found proxies for user satisfaction and retention by having a mental causal structure model that estimates the utility of an experience to users.

Model User Learning (Hohnhold, O'Brien and Tang 2015)

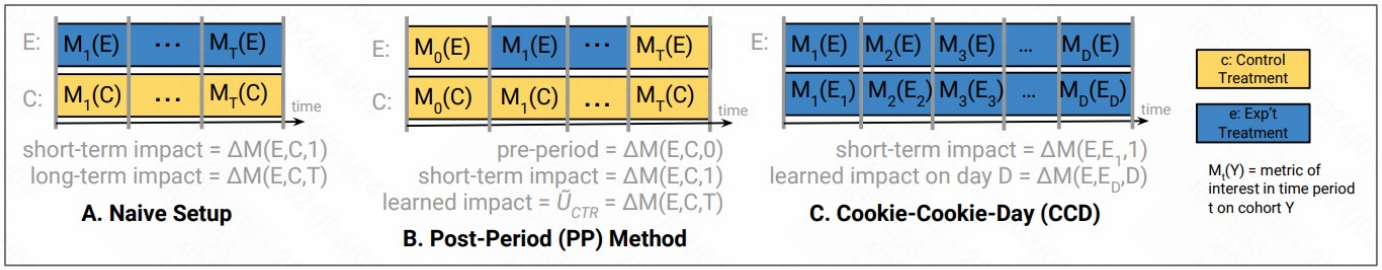


Figure 1: Graphical depiction of the Naive Setup, Post-Period, and Cookie-Cooke-Day methods.

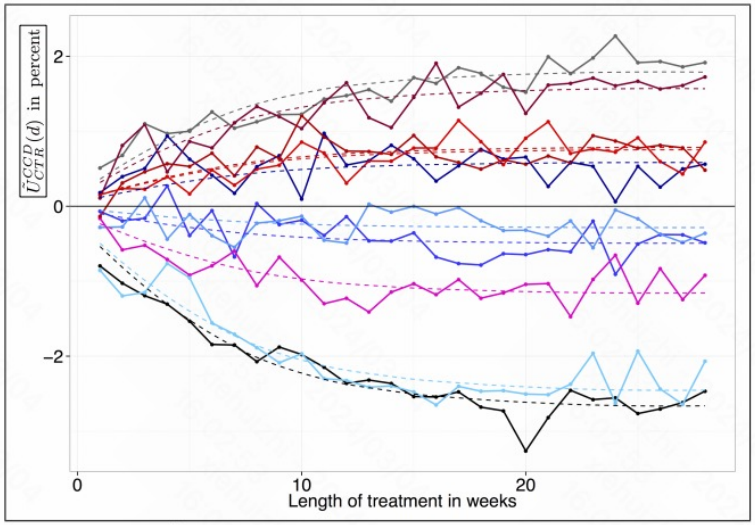


Figure 2: $\tilde{U}^{CCD}_{CTR}(d)$ for a grid of 10 different system parameter changes for mobile devices. The dashed lines give a simple exponential learning model, see Equation (4).

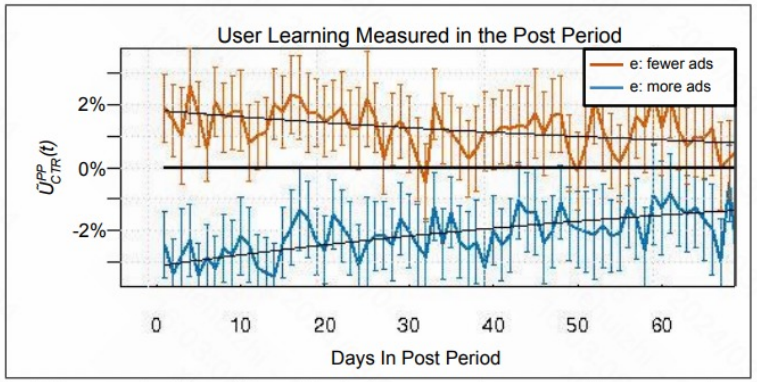


Figure 3: Two Post-Period comparisons to the control.

Model User Learning Cont'd (Hohnhold, O'Brien and Tang 2015)

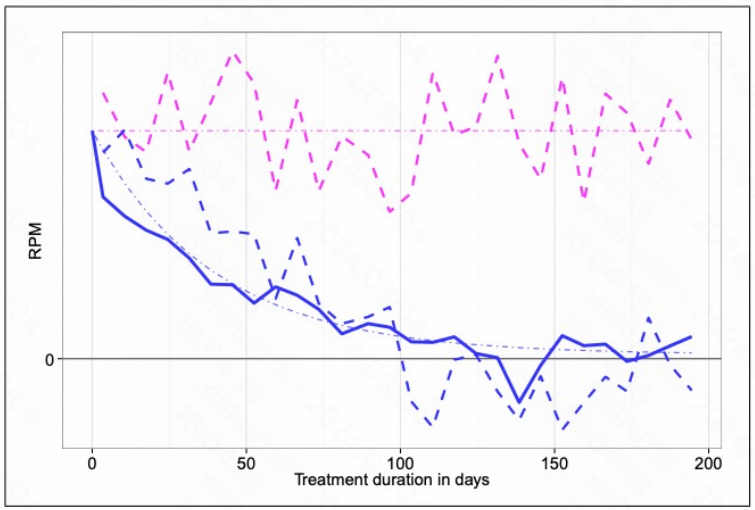


Figure 5: Short-term (pink) and long-term (blue) ΔRPM metrics for simple ad load changes on mobile Google search, restricted to old cookies, 6/26/2013 – 1/9/2014.

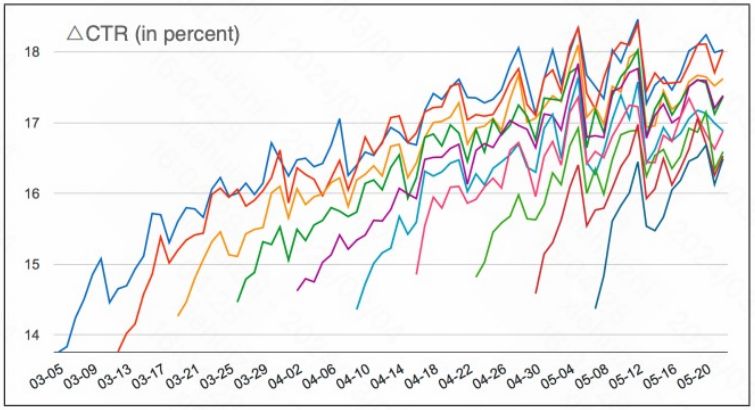


Figure 6: ΔCTR time series for different user cohorts in the launch. (The launch was staggered by weekly cohort.)

A Short Discussion On Surrogates

- A statistical surrogate lies on the causal path between the treatment and the long-term outcome. Condition on the surrogate, the treatment and the long-term outcome are independent.

- Both observational data and experimental data can be used to find good surrogates.

- Example work:
  - The surrogate index: combining short-term proxies to estimate long-term treatment effects more rapidly and precisely. Athey et al. 2019. Facebook used this approach to find good surrogates of the 7-day outcome of an experiment by just using 2-3-day experiment results.
  - Estimating effects of long-term treatments. Huang et al. 2023

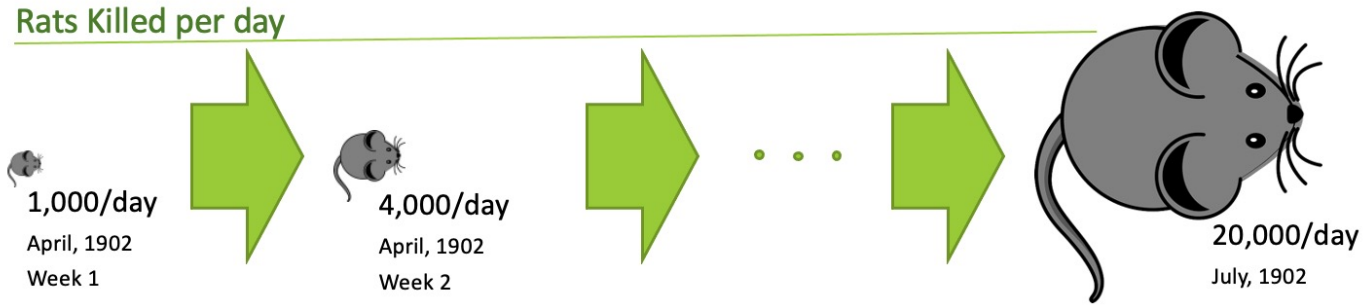
- Having too many surrogates may make this approach less interpretable.

Overall Evaluation Criterion Metric (OEC): **Problem**

- Key properties of a good OEC:
  - Indicative of the long-term gain in key business metric
  - Hard to game and incentivize the right set of actions in the product team
  - Sensitive: easy to move in experiment
  - Cheap to compute
  - …

Finding A Good Metric Is Hard: A Real Life Example

In 1902, the French quarter in Hanoi was overrun with rats. A "deratization" scheme paid citizens for each rat they captured (the proof requested for payment was rat's tail).



But they barely made a dent in the problem!

Two phenomena happened:

1. Tailless rats started appearing
2. A thriving rat farming industry emerged in the city

https://community.redhat.com/blog/2014/07/when-metrics-go-wrong/
http://www.freakonomics.com/media/vannrathunt.pdf
https://en.wikipedia.org/wiki/Cobra_effect

Finding A Good Metric Is Hard: The Microsoft Bing Example

- OEC for search
  - A ranking bug in an experiment resulted in very poor search results
  - Degraded (algorithmic) search results cause users to search more to complete their task, and ads appear more relevant
  - Distinct queries went up over 10%, and revenue went up over 30%
- Analyzing queries per month, we have

$$\frac{Queries}{Month} = \frac{Queries}{Session} \times \frac{Sessions}{User} \times \frac{Users}{Month}$$

where a session begins with a query and ends with 30-minutes of inactivity. (Ideally, we would look at tasks, not sessions).

- In a controlled experiment, the variants get (approximately) the same number of users by design, so the last term is about equal
- Key observation: we want users to find answers and complete tasks quickly, so queries/session should be smaller
- The OEC should therefore be based on the middle term: Sessions/User

KPIs And Experiment Metrics Are Different!

	KPIs	Experiment Metrics
Purpose	Measure how effectively key business objectives are being achieved **Lagging Metric**	Evaluate specific hypotheses and make ship decisions based on indicators for improvement in KPI **Leading metric**
Format	Often displayed as a single uncontrolled time series in a dashboard	Often displayed as a comparison between treatment and control in a scorecard
Focus	Focus on trends, anomalies, and comparisons against targets	Focus on statistically significant deltas between treatment and control groups
Time period	MoM, QoQ, YoY	1 week, 2 week
Granularity	Measured in aggregate	Measured for each user in the experiment

Heterogeneity In Treatment Effects (HTE): **Problem**

- The primary goal of an A/B test is to understand the average treatment effect.
- It is ideal to know individual treatment effect.
- Knowing individual treatment effect is not possible because we cannot observe the counterfactual.
- The closest to individual treatment effect is conditional average treatment effect.

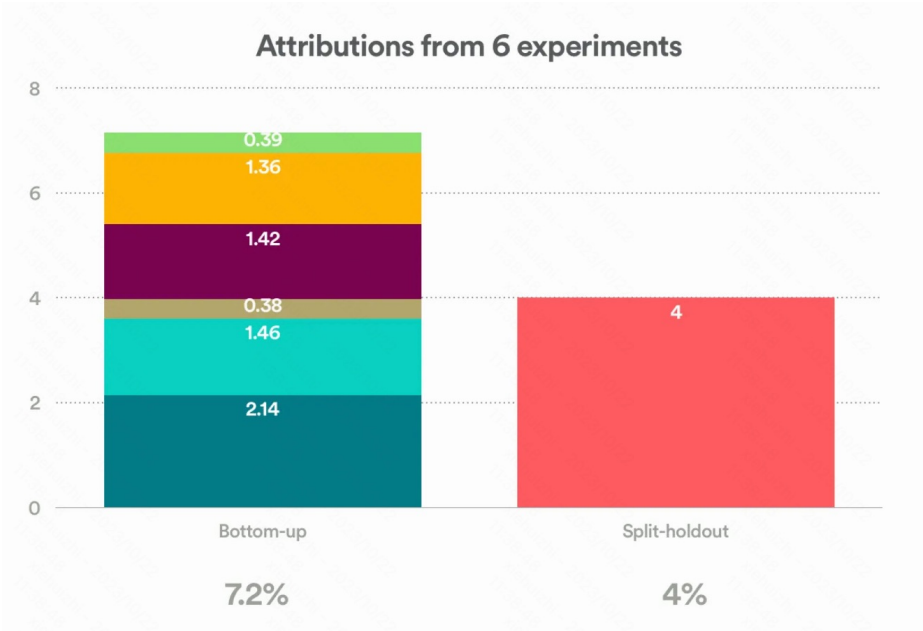
Heterogeneity In Treatment Effects (HTE): Common Solutions And Challenges

- Solution:
  - Common user segments
    - Market/country
    - User activity level
    - Device and platform
    - Time and day of week
    - ...
  - Machine learning models: Athey et al.'s honest decision tree and random forest

- Challenge:
  - Computation scale
  - Low signal-to-noise ratio
  - Multiple testing
  - Interpretable and memorable results

Aggregated Effect Of Multiple Experiments: Problem (Shen and Lee 2018)

Winner's curse: estimated effect of launched experiments is higher than the true effect.



Aggregated Effect Of Multiple Experiments: Solution (Shen and Lee 2018)

- Set of experiments with statistically significant effects: $A = \{i | X_i / \sigma_i > b_i\}$
- True aggregated effect of experiments in A: $T\_A = \sum\{i \in A\} a_i$
- Estimate of true aggregated effect of experiments in A : $S\_A = \sum\{i \in A\} X_i$
- A is a random set, so in gener$\mathrm{E}S_A \neq \mathrm{E}T_A$
- In fact, $\mathrm{E}S\_A \geq \mathrm{E}T\_A$,the proof is as follows:

$$\begin{aligned}\mathbb{E}[S_A - T_A] &= \mathbb{E}\Big[\sum_{i\in A}(X_i - a_i)\Big] = \mathbb{E}\Big[\sum_{i=1}^{n} I(i \in A)(X_i - a_i)\Big] \\ &= \sum_{i=1}^{n} \mathbb{E}[I(i \in A)(X_i - a_i)] = \sum_{i=1}^{n} \mathbb{E}\Big[I\Big(\frac{X_i}{\sigma_i} > b_i\Big)(X_i - a_i)\Big] \\ &= \sum_{i=1}^{n} \mathbb{E}[I((X_i - a_i) > (b_i\sigma_i - a_i))(X_i - a_i)].\end{aligned}$$

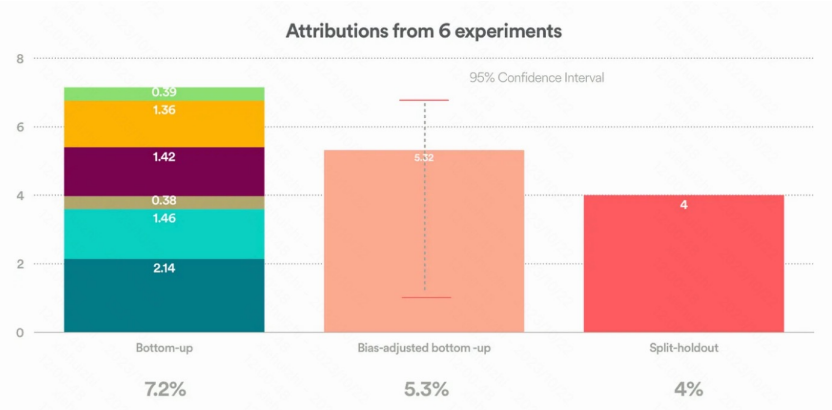
Aggregated Effect Of Multiple Experiments: Solution Cont'd (Shen and Lee 2018)

- Bias:

$$\beta = \mathbb{E}[S_A - T_A] = \sum_{i=1}^{n} \sigma_i \phi\left(\frac{\sigma_i b_i - a_i}{\sigma_i}\right)$$

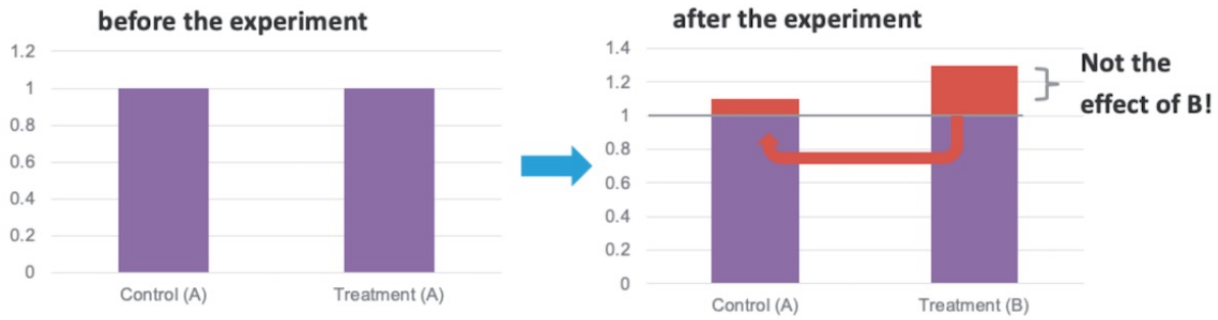
- Estimate of bias:

$$\hat{\beta} = \sum_{i=1}^{n} W_i \phi\left(\frac{W_i b_i - X_i}{W_i}\right)$$



Network Effects: Problem

- The stable user treatment value assumption (SUTVA) is violated because of user non-independence.



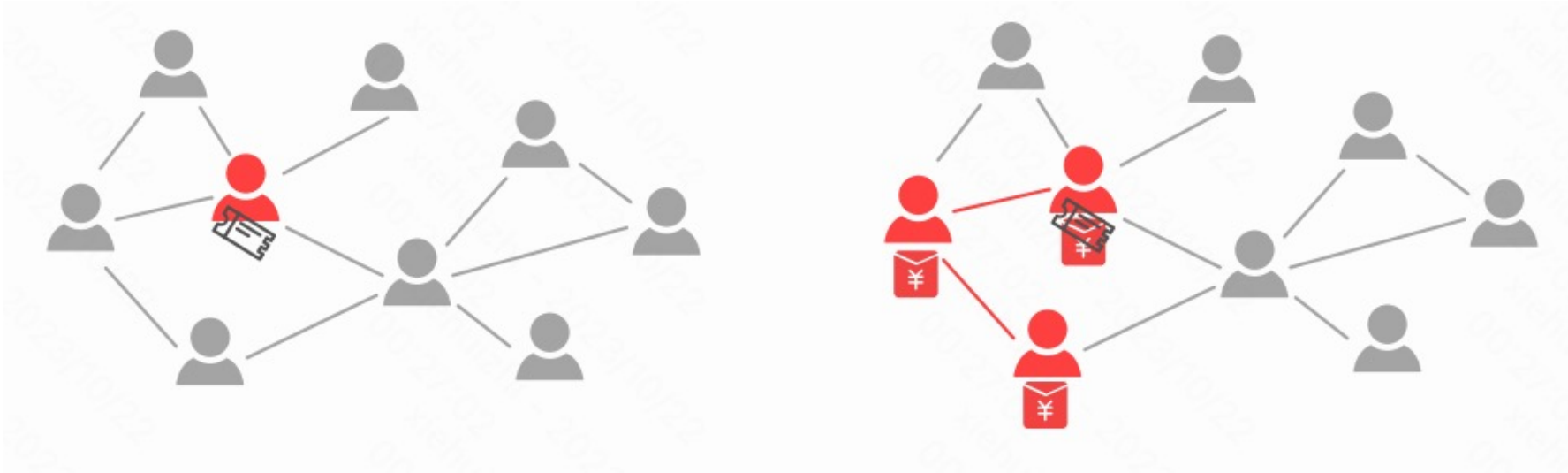
A/B testing with interference. When treatment leaks into control, we can no longer rely on computing mean(B) – mean(A).

https://engineering.linkedin.com/blog/2019/06/detecting-interference--an-a-b-test-of-a-b-tests

Network Effects: Common Solutions

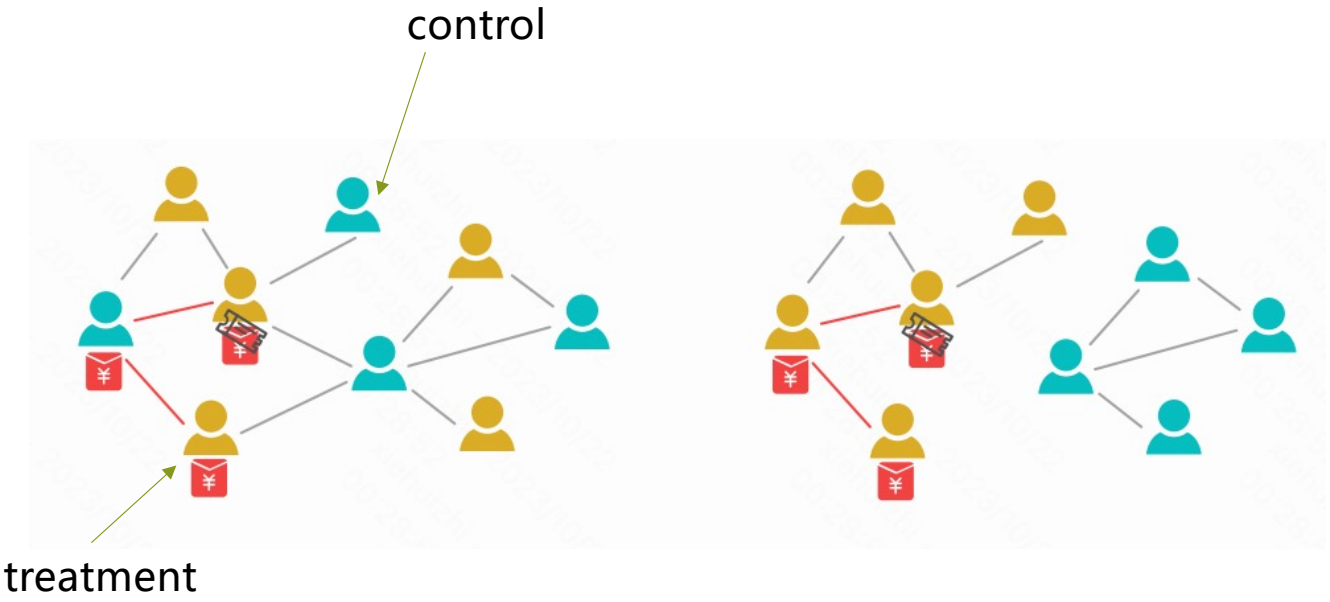
- Producer and consumer model: two-sided randomization
- Known influence network model: randomization at user-cluster level
- One-to-one communication: randomization at call level, causal inference based on observational data
- Market effects: randomization at user-cluster level, equal budget split for ads experiments
- Multiple identities for the same person

Known Influence Network Model: Ant Group's Person-to-person Spread Marketing Strategy (Cai et al. 2021)



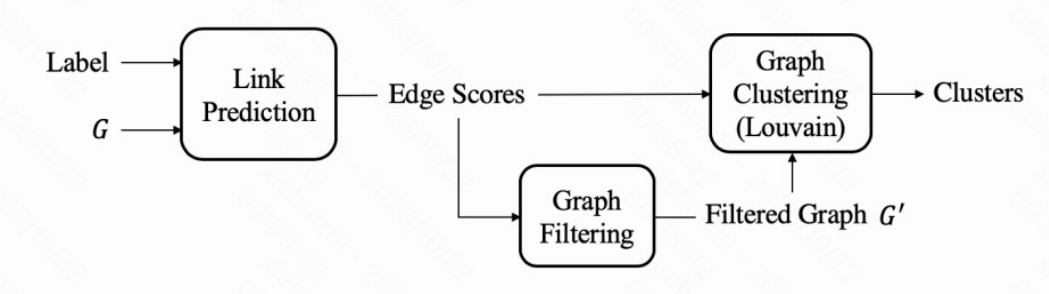
Inviter and invitee both get cash incentive.

Treatment Effect Based On User-level Randomization Is Biased. (Cai et al. 2021)



Cluster Level Randomization Improves Accuracy Of The Treatment Effect Estimate By 50%. (Cai et al. 2021)

1. LinkLouvain clustering:



2. Cluster level randomization

3. Delta method to estimate the variance of user-level metrics

Interaction Between Experiments: Problem

- Let *T1* and *T2* be two treatments in two experiments. If $ATE(T_1) + ATE(T_2) \neq ATE(T_1T_2)$, then we say there is interaction between *T1* and *T2* .
- Textbook example: *T1* changes the foreground color to blue, *T2* changes the background color to blue.

Interaction Between Experiments: Common Solution

- The layer system: experiments that interact with each other run on the same layer.
- Automatic detection of interaction effects between experiments that run on different layers concurrently

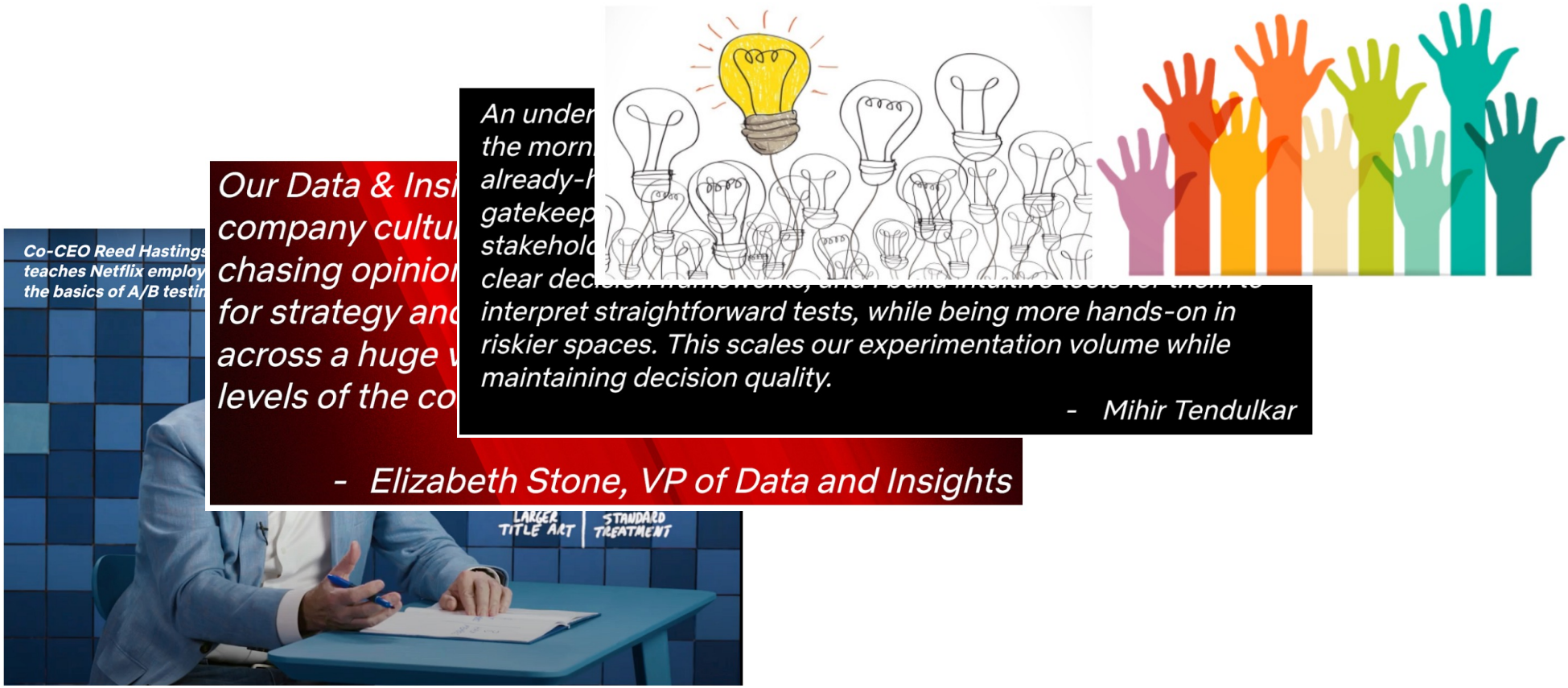
Developing Experimentation Culture: **Problem**

- It can be hard to subject one's idea to experimentation and receive negative feedback. It feels like someone telling you that your baby is ugly.
- Experimentation culture development stages:
  - Hubris: every idea is considered a winner
  - Skepticism: some experimentation is run and intuition challenged
  - Humility: coming up with ideas that work is not easy
- It is ideal to see experiments with positive results. But experiments with negative results are also of great value:
  - Avoid rolling out worse experience to users
  - Better understanding of users and product

Developing Experimentation Culture: Common Solution

- Experimentation platform and tools: improve experimentation speed
- Practices, policies, and capabilities:
  - High touch: by quarter, experimentation team works with critical business team
  - Top down buy in
  - Negative and positive case studies
  - Safe rollout: work with engineers
  - Report cards and gamification
  - Education and support

Netflix's Learning Culture



https://netflixtechblog.com/netflix-a-culture-of-learning-394bc7d0f94c

Training Others To Scale Experimentation: **Problem**

- The concept of A/B testing is simple. But there can be complex practical issues that cannot be standardized and solved by platform or a set of FAQs.
- Centralized team does not scale very well.
- Practical challenges in spreading expertise about experimentation that enable experimentation at scale:
  - How do we set up a community to support experimenters?
  - How do we incorporate them in the experiment lifecycle?
  - How do we incentivize these people?
  - How do we quantify their impact?
  - How do we train them?
  - How do we maintain quality standards?

Training Others To Scale Experimentation: **Common Solution**

- Yandex's "*Experts on Experiment*" program: handpicked from product team by the central experimentation group
- Amazon's "*Weblab Bar Raisers*" program: high-judgment and experienced experimenters
- Twitter's "*Experiment Shepherds*" program: including CTO, around 50 members, pre-test and pre-launch review
- Booking.com's "*Experimentation Ambassadors*" program: handpicked by the central experimentation group, around 15 members, work with a support ticketing system to provide experimentation consulting service
- Microsoft's "*Center of Excellence Model*": the data science team in the central experimentation group provide consulting service
- Google's "*Just-in-time Education Model*": checklist, experiment council

There Are More Practical Challenges.

- Continuous decision-making: sequential testing
- Multiple metrics, experiment groups inference: multiple testing
- Intelligent traffic allocation: multi-arm bandits, connected to reinforcement learning
- Causal inference scenarios where experimentation fails or is too costly: natural experiments, observational data causal inference
- The application of large language models in experimentation
- …

/04 Takeaway

Key Takeaway

- Internet company builds product/service for its users. Data-driven operation improves the efficiency of value delivering to users, thus the efficiency of continuous growth.
- Metric and causal inference are two key elements for data-driven operation to work.
- Causal inference is not easy. A/B testing is the gold standard for causal inference.
- The concept of A/B testing is simple, but the practice is hard, 1/3 is about business and user understanding, 1/3 is about engineering, 1/3 is about science.

Let's End With Kohavi's Quote.