# A/B Testing I

THE INTELLIGENT FUTURE

**Mini 4 / Spring 2024**

Carnegie Mellon University
Tepper School of Business

# Upcoming Guests

- Mon, April 8
  - Guest speaker: **Sachal Lakhavani (AI Product Manager @ Meta; Tepper MBA alum)**
  - 30 min Q&A about A/B testing & Product management (Section A: 5-5:30pm, Section E: 6:30-7pm)
  - Everyone is expected to prepare for at least one question (I might cold call!)
  - 15 min 1:1 Q&A (Section A: 5:30-5:45pm, Section E: 7-7:15pm)
- Mon, April 15
  - Guest speaker: **Michael Degnan (Senior VP, Head of Enterprise Innovation @ PNC)**
  - 1 hour lecture on New Product Development & Innovation
  - 30 min Q&A about Innovation & Product management

# Final Project Presentations

- Schedule
  - Section A: Wed, April 17 (Teams 1-3) & Mon, April 22 (Teams 4, 5, 7)
  - Section E: Mon, April 15 (all teams)
- Deliverables
  - 20 min presentation & slides (no min/max requirement)
  - Submit the slides to Canvas by the beginning of Wed, April 17 (Section A) or Mon, April 15 (Section E)
- Logistics
  - Each team should ask at least one question for other teams' presentations
  - **Attendance is expected for all teams' presentations**

# Final Project Presentations

- Product selection
  - Approved on Canvas; Let me know if you are not happy with the current selection
- Required
  - What is the Problem a product manager is facing (WFH or GenAI)
  - Environment analysis (e.g., 3C)
  - Customer needs discovery (e.g., interview, UGC, survey; please define your target segment)
  - **(At least one) Feature proposal** (show us what features you considered; connection with customer needs is essential; please consider the AARRR framework)
  - Design of A/B testing to assess the proposed feature
- Optional
  - Frameworks from the pre-class videos (e.g., RICE)
  - Qualitative/quantitative insights (e.g., from market reports, data, your own experiences)

# Schedule Going Forward

- Section A

| | Monday | Wednesday |
|---|---|---|
| Week of 4/1 | A/B testing 1 | A/B testing 2<br>(cases: Uber Pool, Booking.com) |
| Week of 4/8 | A/B testing 3<br>**Guest Q&A (Sachal Lakhavani, Meta)** | Product Growth, Acquisition and Retention (case: Blue Apron) |
| Week of 4/15 | **Guest lecture (Michael Degnan, PNC)** | Presentations |
| Week of 4/22 | Presentations & Wrap-up | |

# Schedule Going Forward

- Section E

| | Part A | Part B |
|---|---|---|
| 4/1 | A/B testing 1 | A/B testing 2<br>(cases: Uber Pool, Booking.com) |
| 4/8 | **Guest Q&A (Sachal Lakhavani, Meta)**<br>A/B testing 3 | Product Growth, Retention, Monetization (case: Blue Apron) |
| 4/15 | **Guest lecture (Michael Degnan, PNC)** | Presentations & Wrap-up |

# RECALL: LAST CLASS

- Product Feature Strategy
  - AARRR Funnel
  - 3 Product Feature Decisions: Adding, Improving, or Killing Product Feature
  - Headspace Case Study

# LOOKING FORWARD: WHAT WILL WE COVER

- "Problem Space" - Pre-Launch of Product Feature
  - Customer Needs Identification
  - Customer Needs Downselection to Primary Needs
  - Quantitative "Importance" of Primary Needs and Needs Prioritization
  - Market Segmentation and Total Addressable Market (TAM) estimation
  - Competitive Analysis, Opportunity Sizing, and Targeting
  - Feature Prioritization
  - Product Requirements Document (PRD) and User Stories
- Post-Launch of Product Feature + Product Strategy
  - A/B Testing
  - Product Growth Strategy
  - Acquisition, Product-Channel Fit
  - Tradeoffs of Acquisition, Retention, and Monetization

# What is A/B Testing?

## Question: who here has run an A/B test before? When and why?

# Example of product feature A/B test: Behavior-based search at Amazon

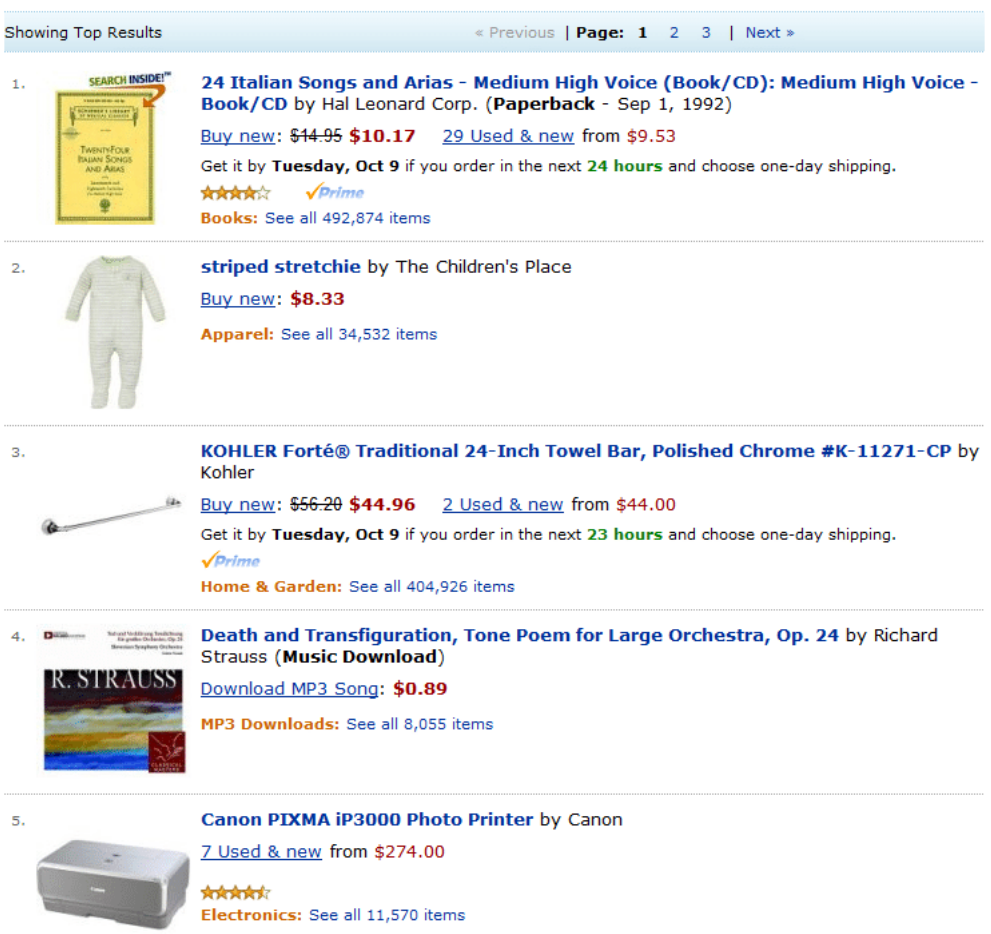
- Product Feature A/B Test
  - Does “Behavior-Based Search” increase eventual purchases?
  - Behavior-Based Search (BBS): People who *searched* for X bought item Y.

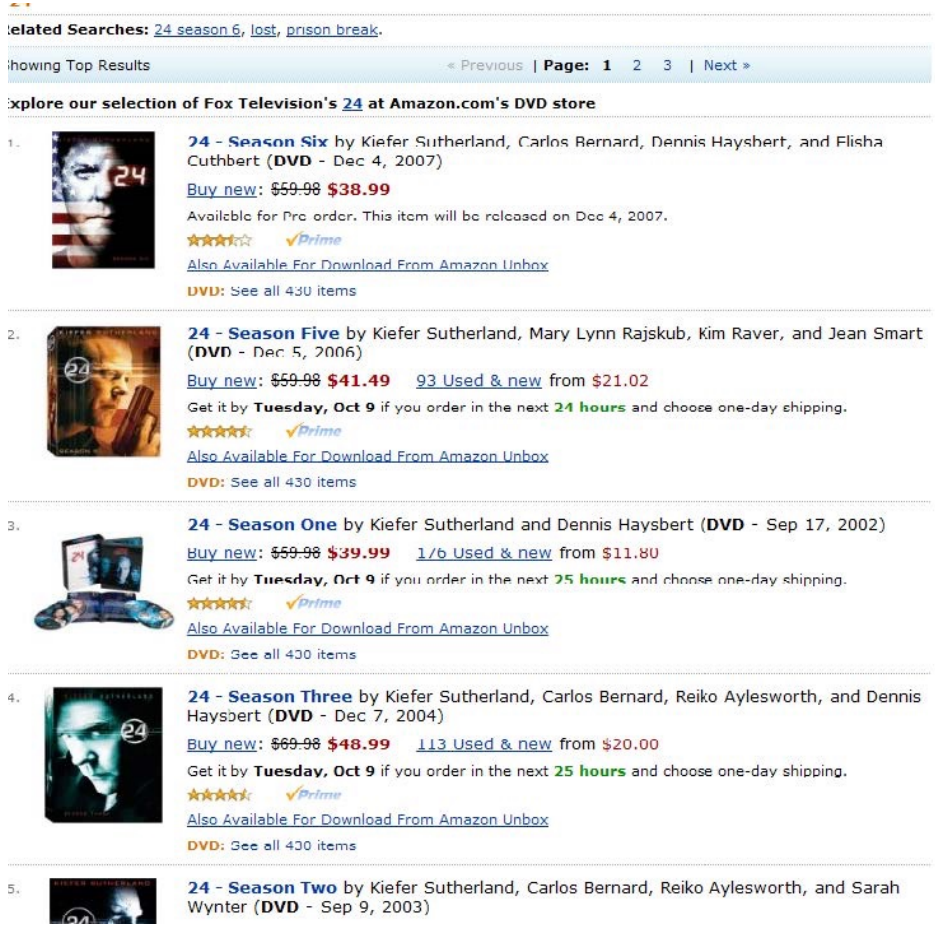
- Example: Search for “24”
  - Amazon found consumers associated it with a Fox TV series
  - w/o BBS: CDs with 24 Italian songs, a 24-inch towel bar, etc.
  - w/ BBS: DVDs of the show, related books, etc.

- Note: Experimentation = A/B Testing

"Our success at Amazon is a function” of how many experiments we do per month, per week, per day.”
- Jeff Bezos, Former CEO, Amazon

Kohavi, R., Longbotham, R., Sommerfield, D., & Henne, R. M. (2009). Controlled experiments on the web: survey and practical guide. *Data mining and knowledge discovery*, *18*(1), 140-181.



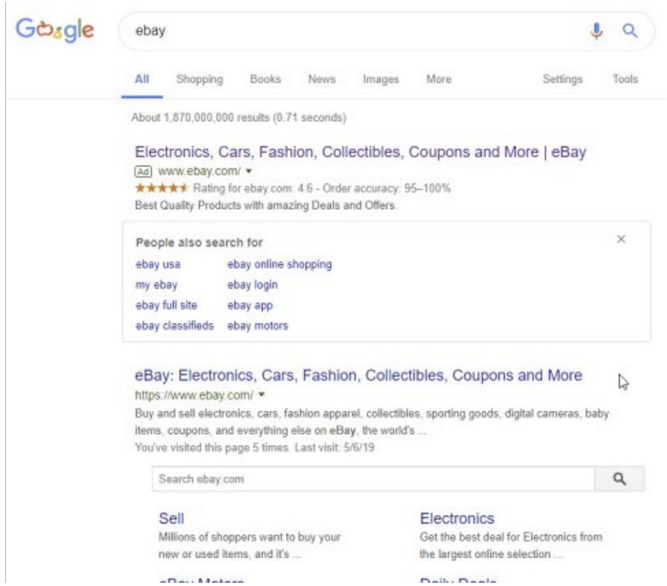



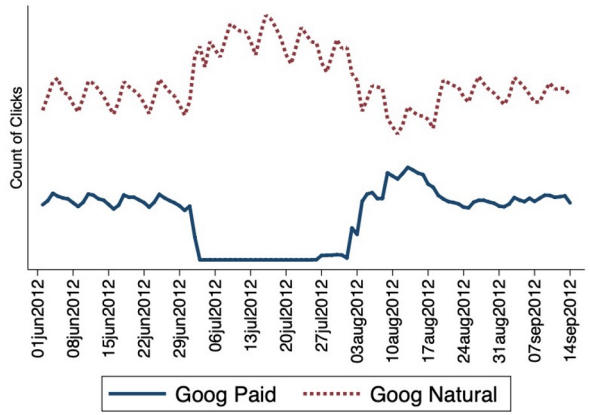

- Outcome
  - 3% increase Amazon Revenue

Kohavi, R., Longbotham, R., Sommerfield, D., & Henne, R. M. (2009). Controlled experiments on the web: survey and practical guide. *Data mining and knowledge discovery*, *18*(1), 140-181.

# ANOTHER EXAMPLE: EBAY ADS ON GOOGLE

- Do Google Ads increase eBay visits?
  - 10% of total site traffic came from Google Ads
  - $300 million on Google AdWords per year
- A/B Test: Stop paying for Google Ads
  - What happened?




(b) Google Test

Blake, T., Nosko, C., & Tadelis, S. (2015). Consumer heterogeneity and paid search effectiveness: A large-scale field experiment. Econometrica, 83(1), 155-174.

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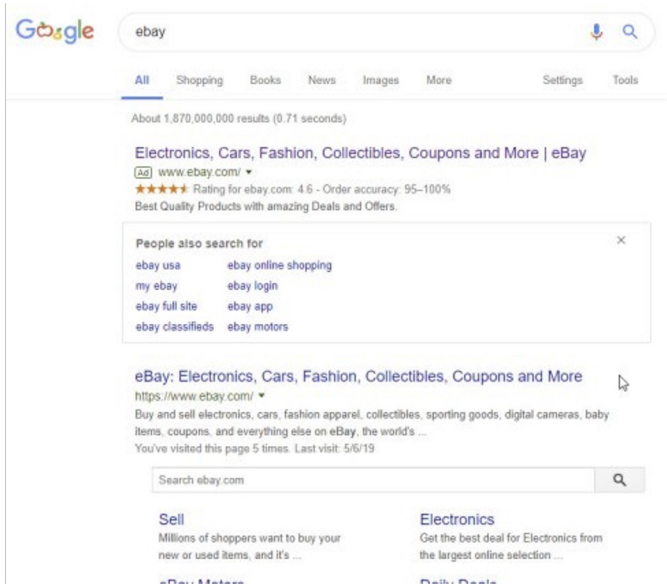
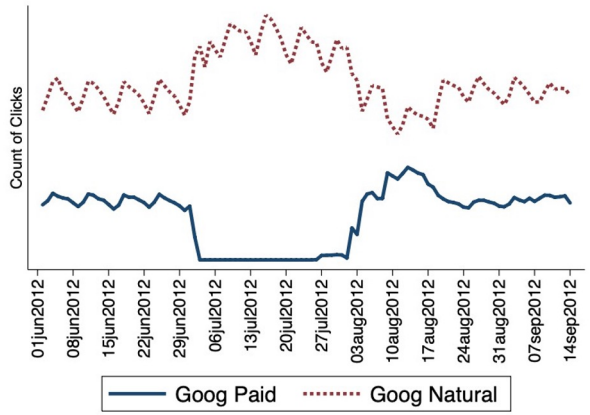
# ANOTHER EXAMPLE: EBAY ADS ON GOOGLE

- Do Google Ads increase eBay visits?
  - 10% of total site traffic (2007)
  - $300 million on Google AdWords per year
- A/B Test: Stop paying for Google Ads
  - 99.5% of users clicked on organic search link instead

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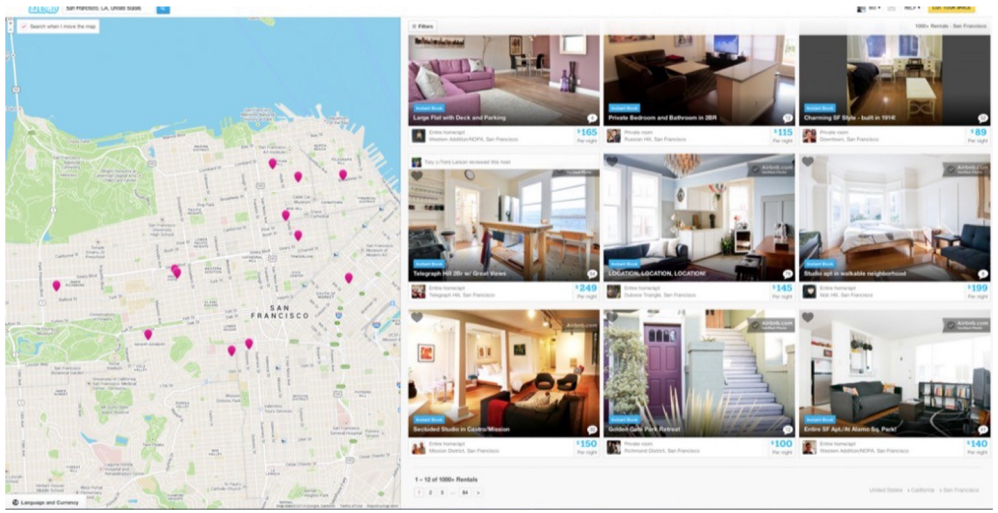
# EXPERIMENTATION IN TECH FIRMS

- Airbnb
  - 500 concurrent experiments / day
  - 2,500 distinct metrics are tracked




```
treatment = user.get_treatment("search_page_number")
if treatment == :12_per_page
  ...
elsif treatment == :18_per_page
  ...
elsif user.country !~ "china" &&
      treatment == :24_per_page
  ...
else
  ...
```

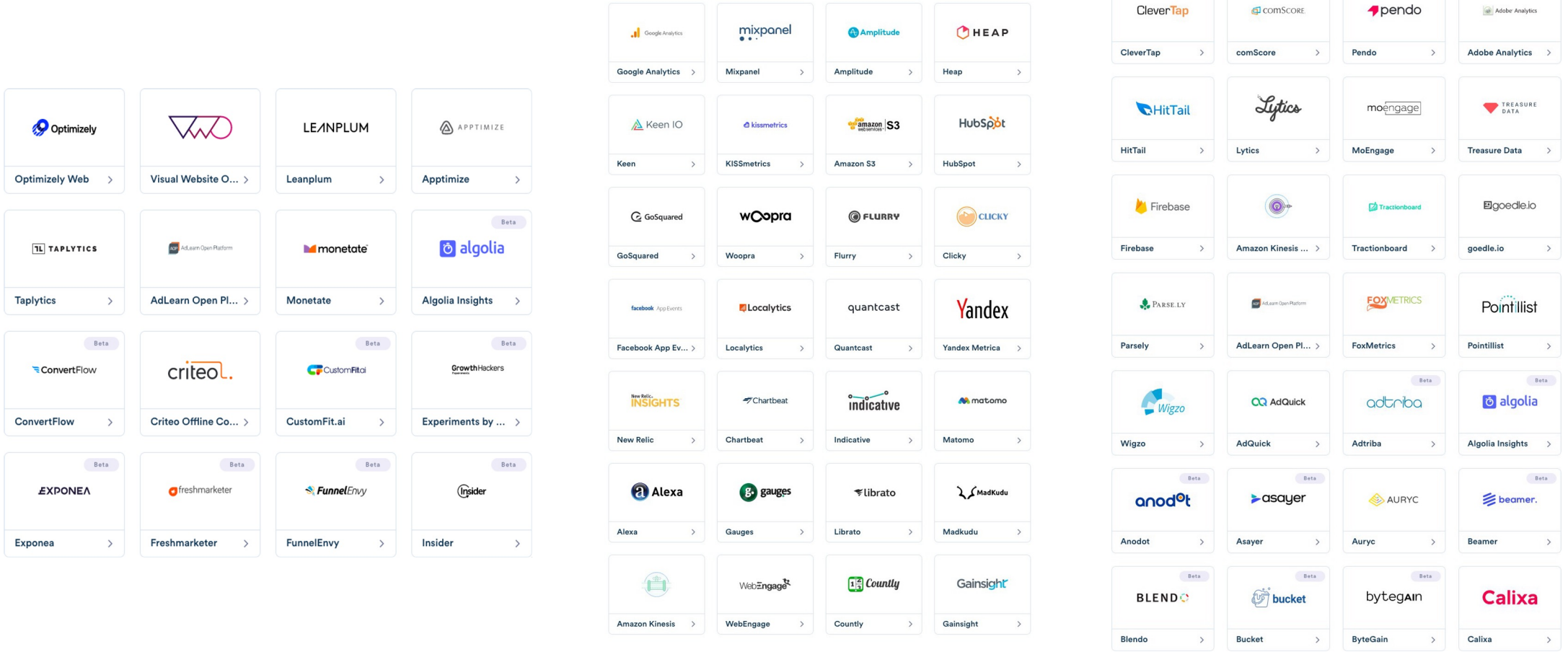
Source: Airbnb Engineering Blog

# MANY TECH FIRMS DO NOT EXPECT "SUCCESS." INSTEAD, THEY HAVE A CULTURE OF EXPERIMENTATION AND CELEBRATE "FAILURES"

- Microsoft
  - < 30% of tested product features successful
  - <10 % for Bing
- Facebook
  - <10%
- Google
  - <10%


Source: https://hbr.org/2017/09/the-surprising-power-of-online-experiments

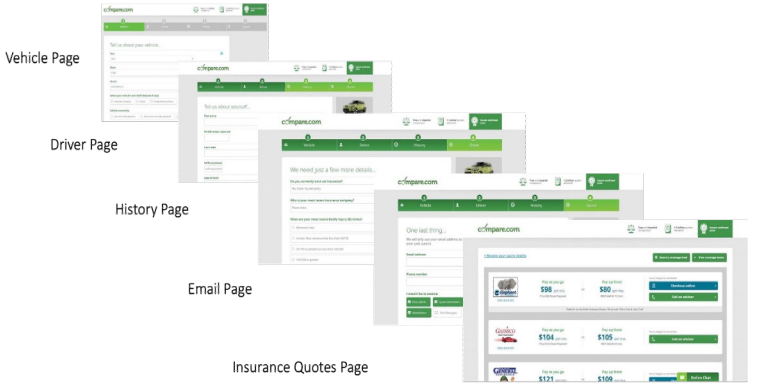
# MANY A/B TESTING TOOLS!

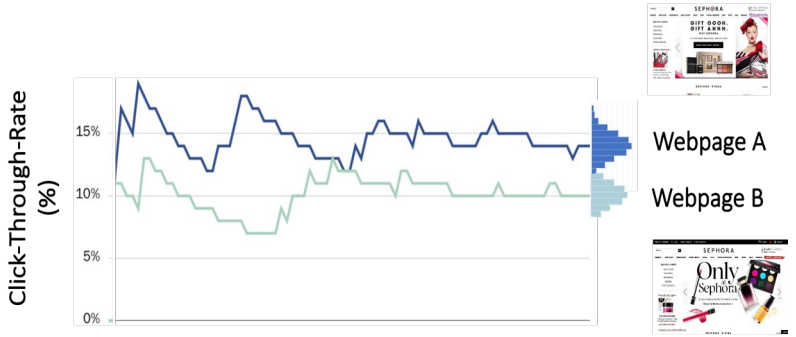


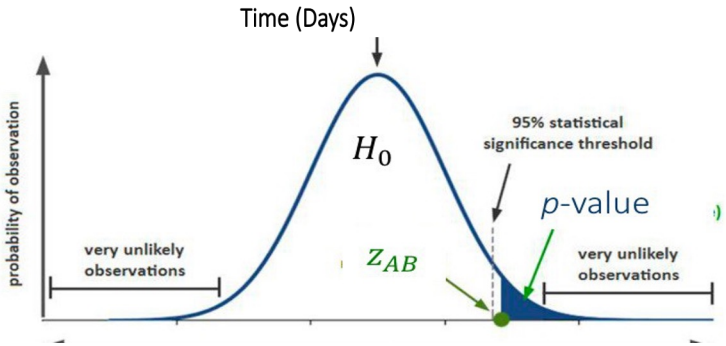

Most important is A/B testing intuition, correct A/B testing setup, how to interpret results, and and knowing how to avoid “common pitfalls”

# TODAY'S LEARNING OBJECTIVES

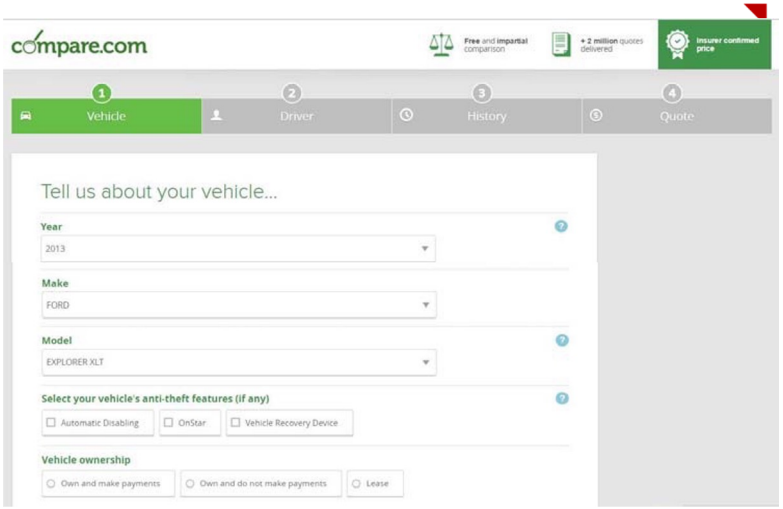
- Motivating Example: Compare.com
- What and Why A/B Test?
  - Focus on Intuition and Definitions
  - 3 Steps for A/B Testing
- How to A/B Test?
  - Statistical Significance
  - Concepts: p-values, confidence intervals, etc.



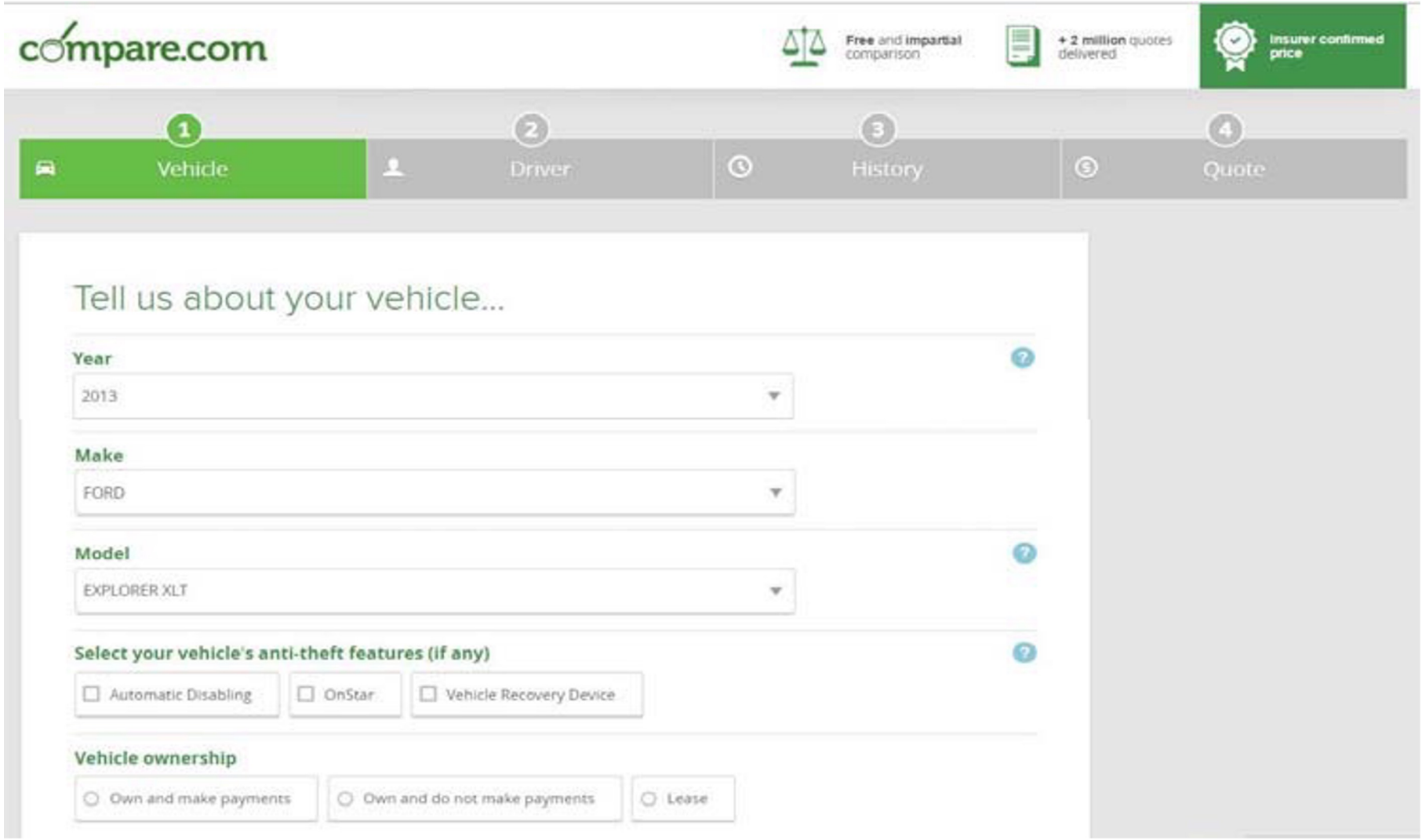



# A TALE OF HIGH CUSTOMER CHURN



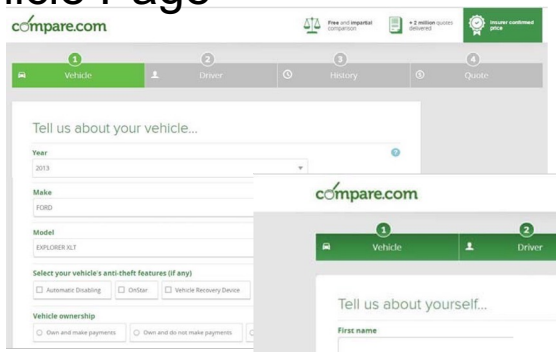

- Compare.com
  - Car insurance comparison website
  - Aggregator: Kayak.com, Hotels.com, Booking.com
- U.S. Car Insurance Market
  - $214.3 billion market value
  - Highly fragmented – over 300 major insurers (e.g., Geico, State Farm)
  - Confusing: 90% customers compare airline tickets, but only 20% car insurance
- Customer Needs
  - Does it mean car insurance quotes are not important for consumer decisions?
  - Why do customers not compare car insurance quotes?
  - What is the result of “not comparing” car insurance quotes?

# A TALE OF HIGH CUSTOMER CHURN

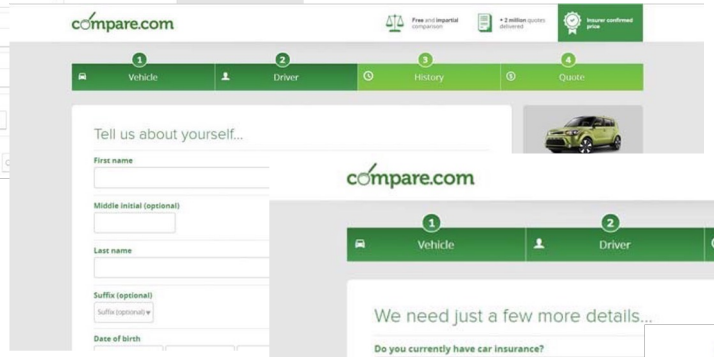


# A TALE OF HIGH CUSTOMER CHURN

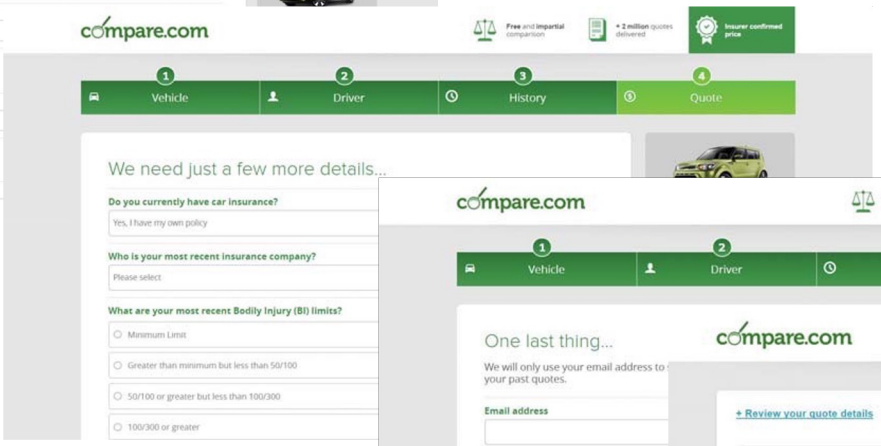
Vehicle Page



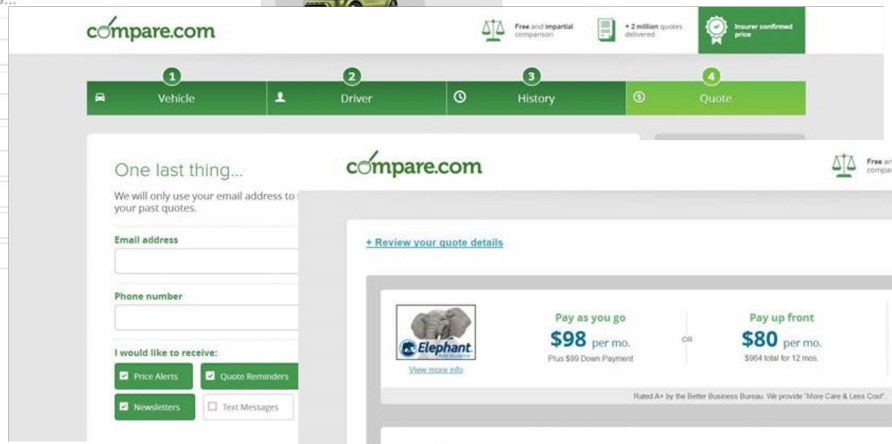

Driver Page



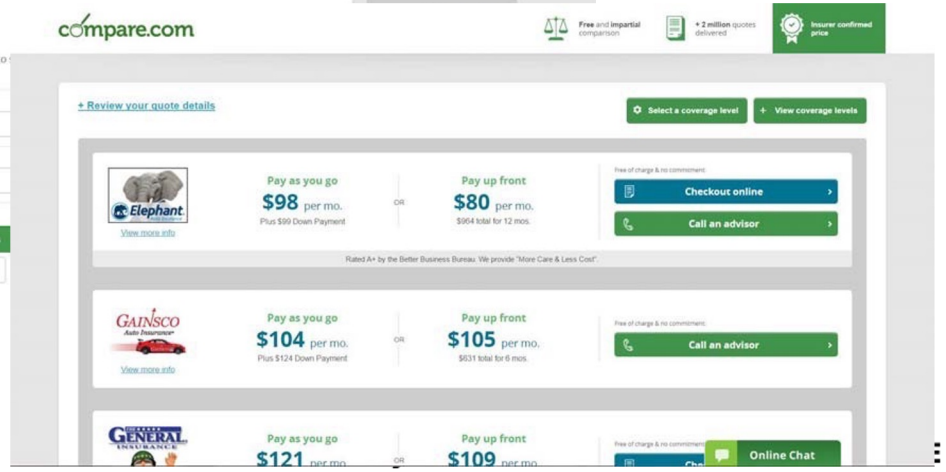

History Page




Email Page




Insurance Quotes Page




## Customer Journey

- 4 website pages before Quotes page
- 31 total questions

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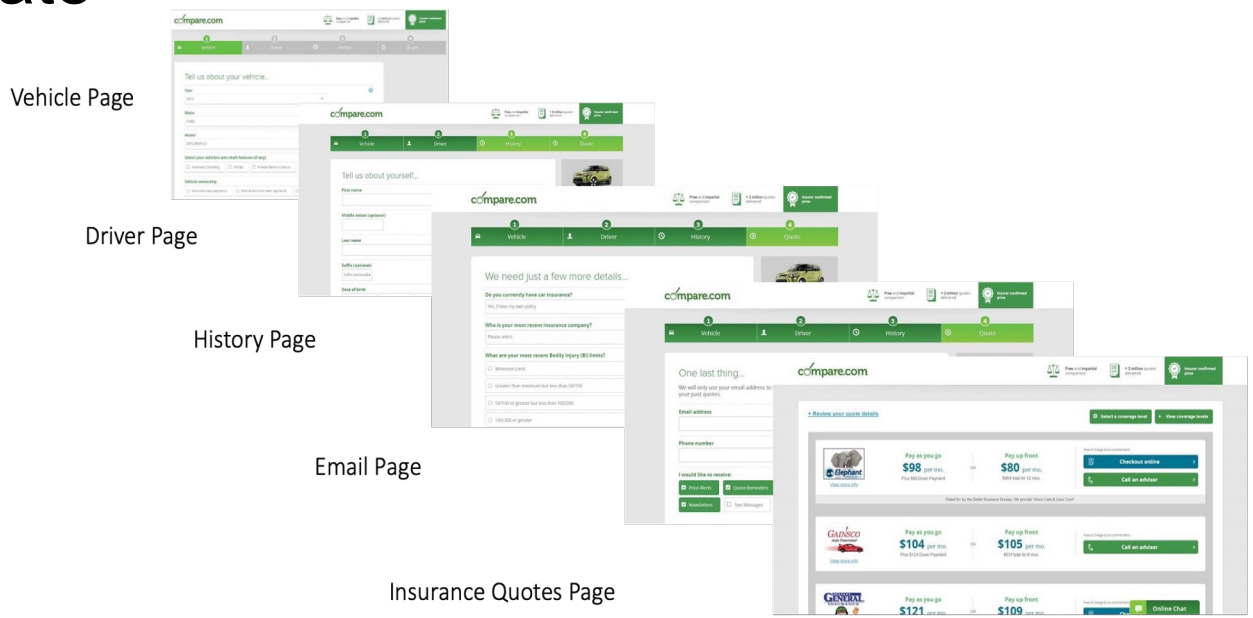
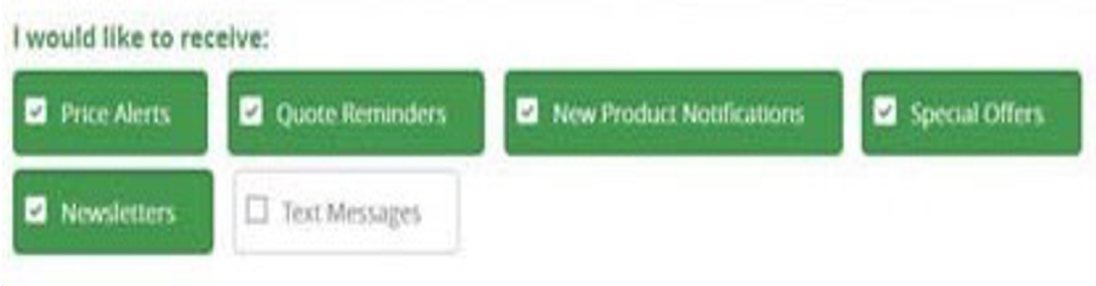
# PROBLEM: LOW COMPLETION RATE

- Metric: New User Completion Rate
  - January 2016 - 18%
  - February 2016 - 13%
  - March 2016 - 12%

- Even after several product changes that slightly increased completion
  - Email page from 1st page to 3rd page
  - Radio buttons for “easy” answers



# IN-CLASS DISCUSSION: LOW COMPLETION RATE

- Your PM team is considering 3 Product Features
  - Option 1) Mobile App
    - Ask users to download mobile app.
    - Complete at time convenient for customer.
  - Option 2) Mid-progress “Saved Quote”
    - Allow customers to save their current progress on quote
    - Email customer so they can complete later
  - Option 3) Website Banner
    - Display early estimate for insurance quote
    - Less information so less accurate


- Question 1: Which feature would you go with? Why?
- Question 2: How would you test the feature?

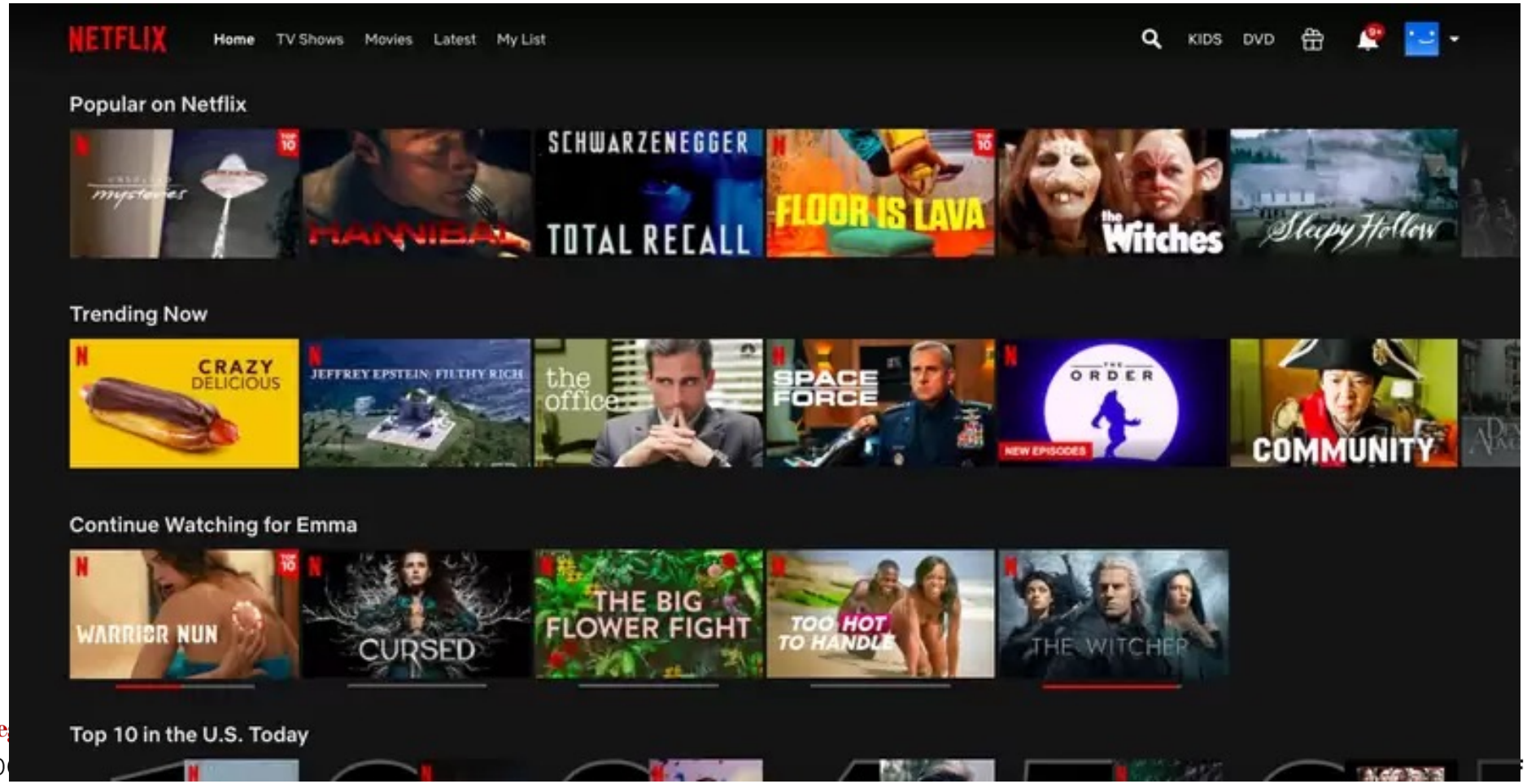
(What is the metric you measure as an outcome? What is the condition A and B? What do you expect from the test?)




https://www.youtube.com/watch?v=WRGW6xHLy3k

# What is A/B Testing?

Let's suppose you are running a A/B test on Netflix main page layouts.



# What is A/B Testing?

Let's suppose you are running a A/B test on Netflix main page layouts.

Question 1: Why is it better than historical data analysis?
Question 2: What is the challenge in testing at scale (Testing many dimensions at the same time)?
Question 3: What's the pros/cons of running tests for all customers vs. a subset of customers (Who would you test)?
Question 4: What metrics you would measure as an outcome?

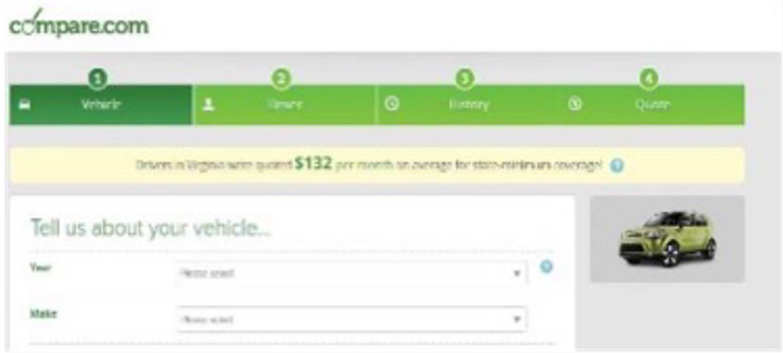
Caitlin Smallwood (VP of Science @ Netflix) in 2021

From 10:46

https://www.youtube.com/watch?v=K4FRu6ilgOA&t=645s

# 3 Steps for A/B Testing

- Step 1) Hypothesis Definition
  - How do we define success or failure (of our product feature)?
  - What metrics do we need to track and measure to test our hypothesis?



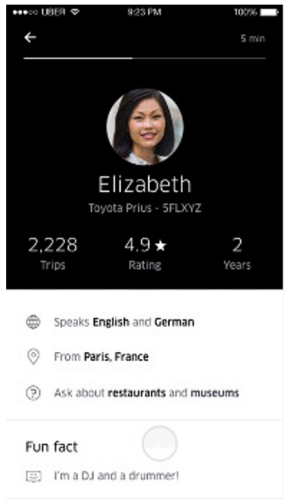

- Step 2) Experimental Design and Launch A/B Test
  - Who do we ask / who should we get data from?
  - How do we ensure we are not getting “biased” results?
  - How many samples do I need? How long to run A/B test?

”Drivers in Connecticut were quoted $_____”

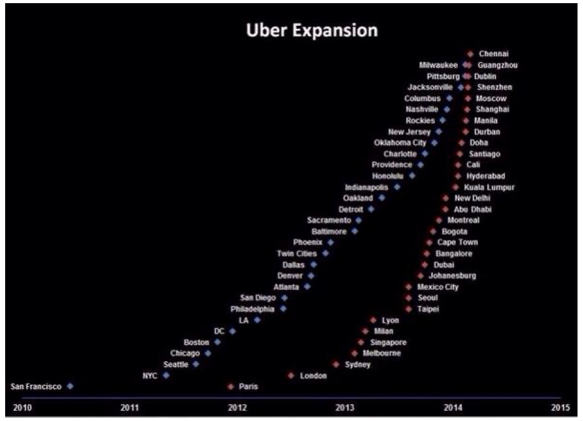
- Step 3) Hypothesis Testing and Interpretation
  - Note: A/B Test = Hypothesis Test
  - What is statistically significant for our test of our hypothesis?
  - Do we go with product feature A or B?

# HYPOTHESIS DEFINITION

- Hypothesis Definition: Written scientific statement on the effect of <improving feature, adding feature, killing feature>
- Example Template: “[Specific repeatable action] will create [expected, measurable result]”
- What makes a “good” hypothesis?
  - Falsifiability – Hypothesis should be able to be quantitatively measured and able to be true or false
  - Generalizability – Hypothesis should be generalizable to cases outside of just the data from the metrics we tracked
- Metrics: Hypothesis defines metrics to track
  - Which (primary, secondary or guardrail) metrics needs to be tracked to “test” hypothesis?




Example Feature: Driver Ratings




Generalizability: Does launching the feature in Houston generalize to Dallas?

# EXAMPLE: HYPOTHESIS FOR RESTAURANT TECH FEATURE

Hypothesis definition for product feature

"[Specific repeatable action] will create [expected, measurable result]"

Feature: "Food pickup feature" for increasing number of orders per day

- *Hypothesis*: Restaurants that add the food pickup feature will increase their overall number of orders per day <by 5%>"
- Metric (to track): Number of orders per day

# EXAMPLE A/B TEST: OBAMA CAMPAIGN LANDING PAGE


A: Original


B: New

- Context: A/B test of two possible "Media" on campaign donation?
- Question: What is the "hypothesis" and metric for this possible change?

# EXAMPLE A/B TEST: OBAMA CAMPAIGN LANDING PAGE


A: Original


B: New

- Context: A/B test of two possible "Media" on campaign donation?
- Question: What is the "hypothesis" and metric for this possible change?
- Hypothesis: The "Change we can believe in with Family in Background" media banner will result in higher donation rates by X%

# EXAMPLE A/B TEST: OBAMA CAMPAIGN LANDING PAGE


A


B

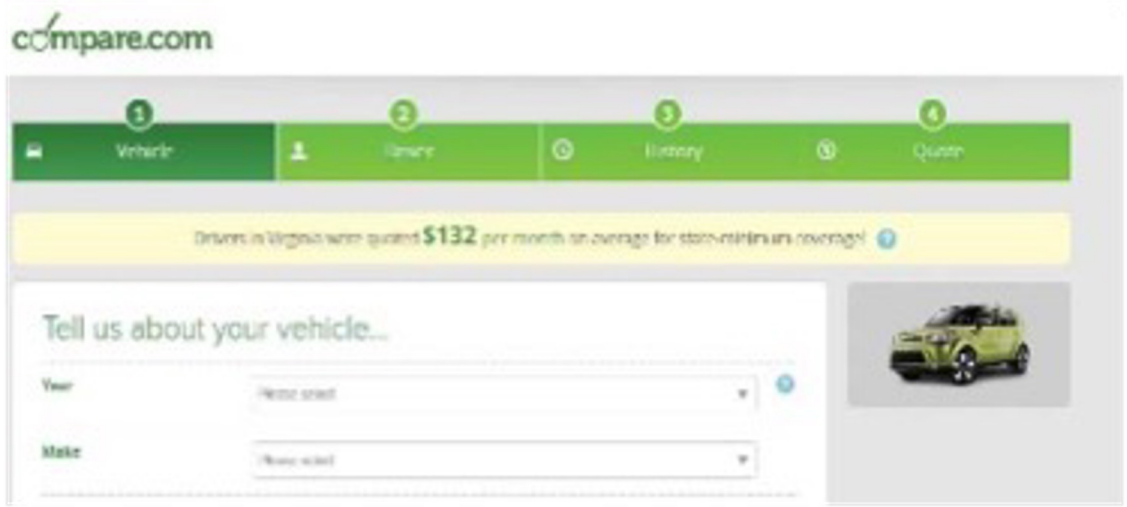
| Media | | | | | |
|---|---|---|---|---|---|
| 5 / 5 | Original | 8.54% ± 0.2% | — | — | 4425 / 51794 |
| | Family Image | 9.66% ± 0.2% | 100% | 13.1% | 4996 / 51696 |

- Hypothesis: The "Change we can believe in with Family in Background" media banner will result in higher donation rates by X% (note: difference between percentage vs. percentage point)


OBAMA'08
CHANGE
WE CAN BELIEVE IN
$60m+
Donations
JOIN THE MOVEMENT
Email Address
Zip Code
LEARN MORE
PAID FOR BY OBAMA FOR AMERICA
CONTINUE to WEBSITE

# A/B TESTING: MANY USE CASES

- Evaluate product features after launch
- Identify bottlenecks and product problem
- Understand differences between how customer segments react to features

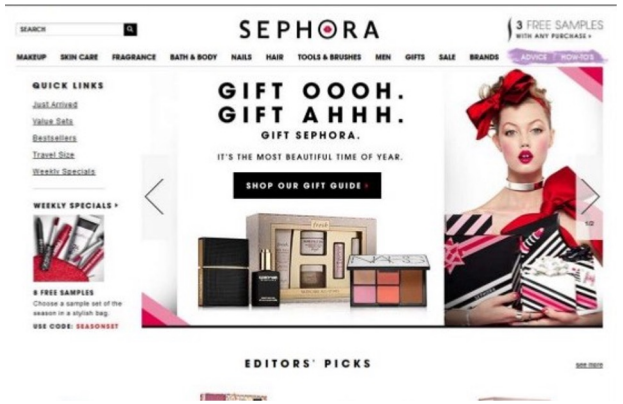


# Intuition:

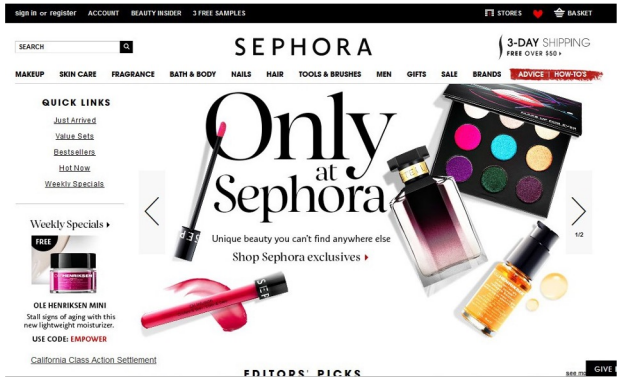
## Why A/B Test?

# EXAMPLE: IMPROVING SEPHORA'S WEBPAGE

- Context: Sephora.com launches new landing site by replacing the old landing site for all users and scrapping the old one.
- Metric: "Click-through-rate" of web page.
- Results
  - Old Webpage 10% click-through-rate (before new site)
  - New Webpage 12% click-through-rate (after new site)
- Question: Should we stay with the new webpage? Why or why not?

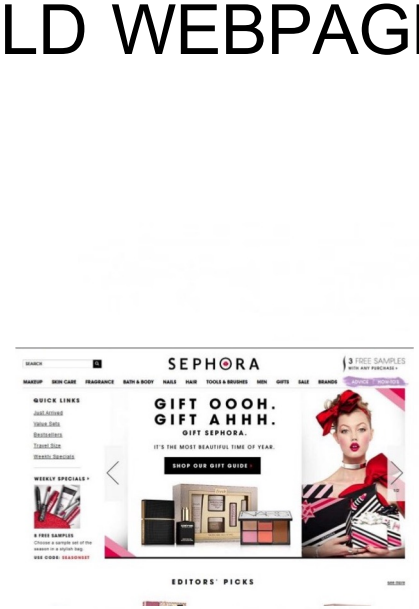


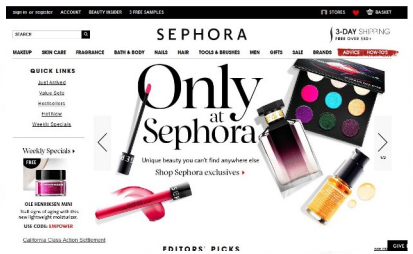

Old Webpage

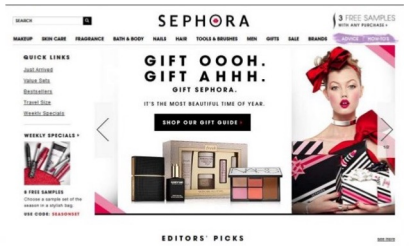



New Webpage

# LET'S SAY WE TRIED THE NEW WEBPAGE,THEN BACK TO OLD WEBPAGE, THEN THIS HAPPENED…







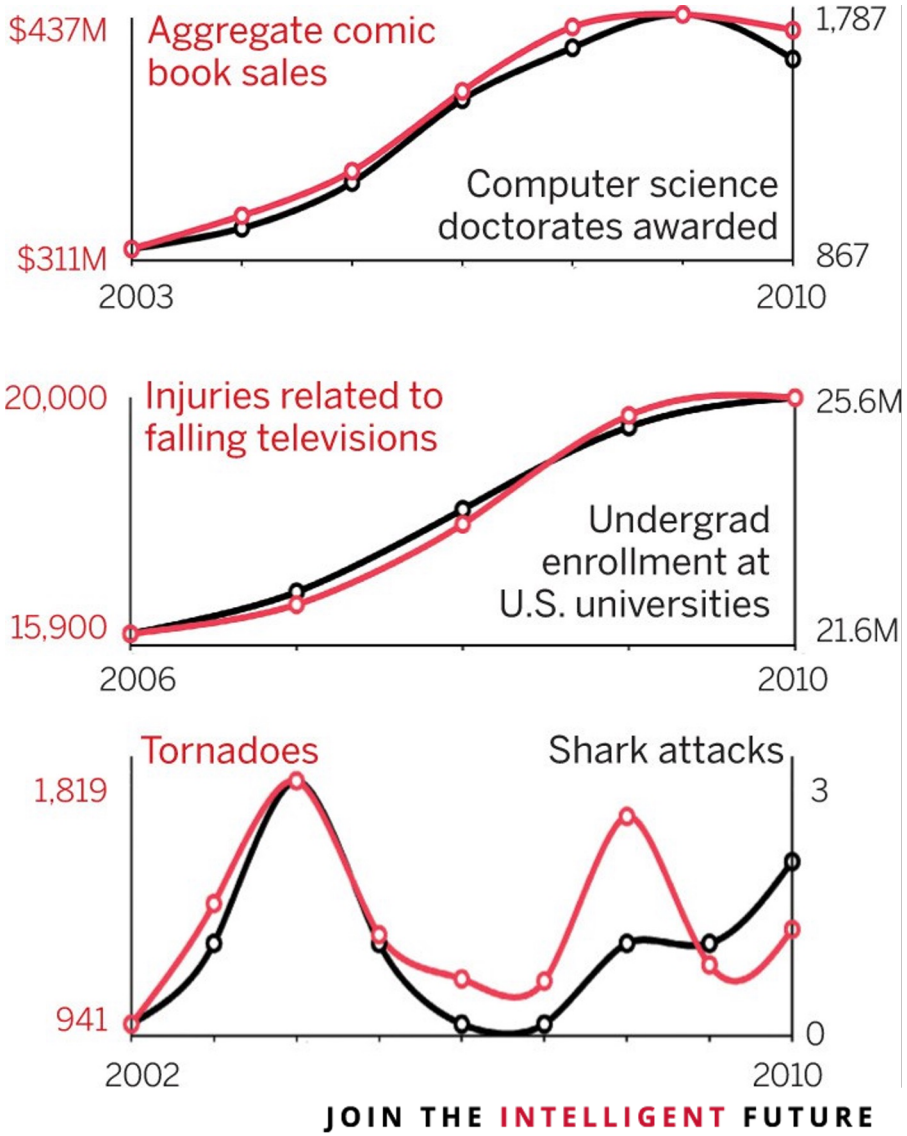
Still going up! Why?

Maybe people are just buying more makeup across all websites…

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

# CORRELATION IS NOT CAUSATION

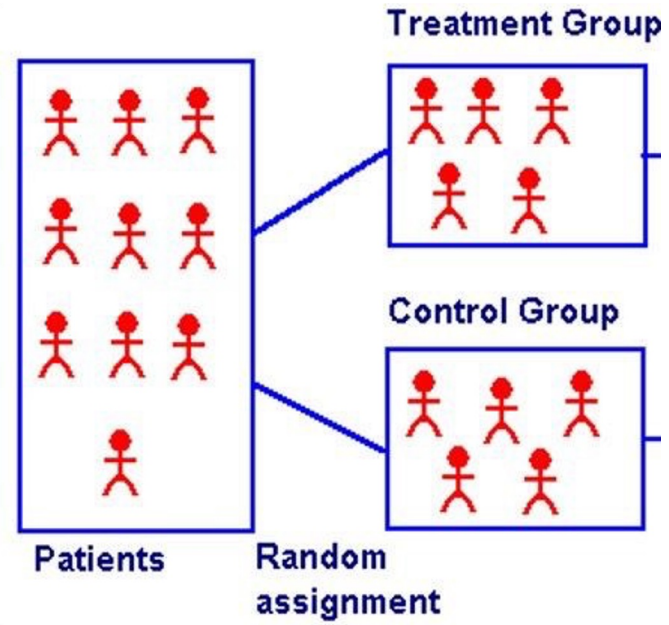
- We can not say the new webpage is better than the old webpage
- The click through rate could simply be higher for any webpage during the time we tested
- We need to control for “unrelated correlation”
- How? Using a ”randomized controlled trial,” also known as an “A/B Test”



# KEY IDEA: TREATMENT AND CONTROL GROUPS

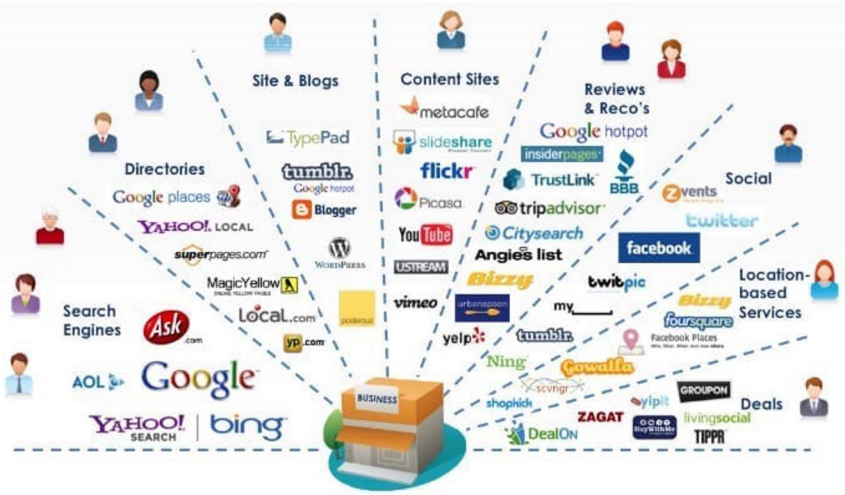
- A/B Test is a "**Randomized controlled trial**"
  - Control Group (Group A) - This group sees no change from the current setup.
  - Treatment Group (Group B) - This group is exposed to the new web page

- Goal of A/B Test
  - Compare the click-through-rates of the two groups using statistical inference.
  - Test our Product Feature "Hypothesis"
  - "[Specific repeatable action] will create [expected, measurable result]"

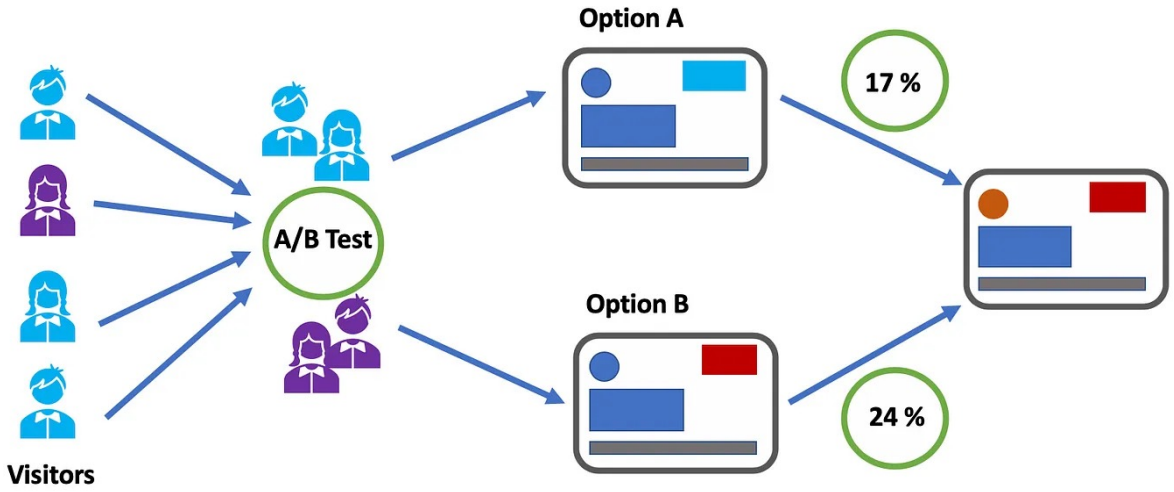


# KEY IDEA: WE "RANDOMIZE" USERS INTO CONTROL (A) AND TREATMENT (B) TO MEASURE CAUSATION (OF OUR PRODUCT FEATURE)

- Why? The world is not a vacuum…
  - More is happening than just the experiment (treatment vs control group) and effect.
- Many "random" situations lead to "biases"
  - Users overall are changing (e.g., buying more makeup).
  - Users characteristics are changing: Different demographics, new vs returning
  - Users have changing goals and intentions: Browsing around, buying immediately, bored and scrolling.
  - Users are finding our webpage differently than before: email, newsletters, web searches, social media
- Key Point: Randomization of users into treatment (A) and control (B) helps balance these out.



# Topic Presentation: Team 4 (Section A) & Team 3 (Section E)

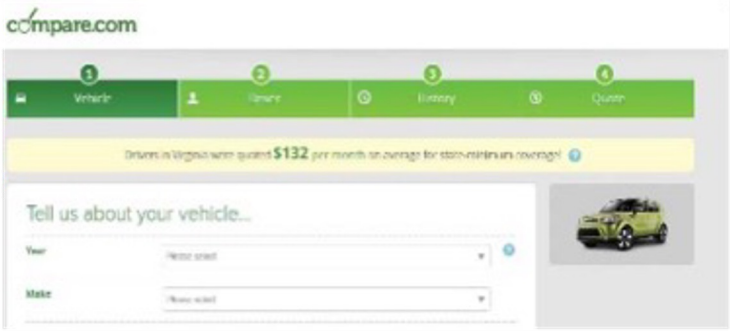



- Netflix A/B testing for its Recommendation algorithm

https://www.youtube.com/watch?v=wc5MNTKLnns&t=275s

# RECALL: 3 STEPS FOR A/B TESTING

- Step 1) Hypothesis Definition
  - How do we define success or failure (of our product feature)?
  - What metrics do we need to track and measure to test our hypothesis?



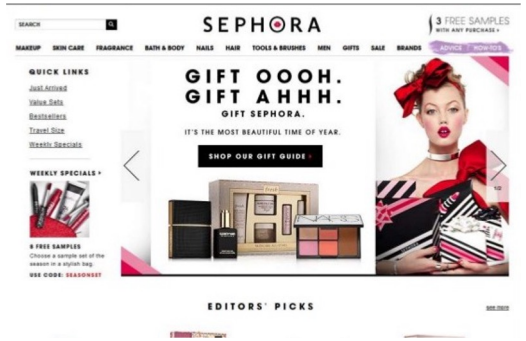

- **Step 2) Experimental Design and Launch A/B Test**
  - Who do we ask / who should we get data from?
  - How do we ensure we are not getting "biased" results?
  - How many samples do I need? How long to run A/B test?

"Drivers in Connecticut were quoted $_____"

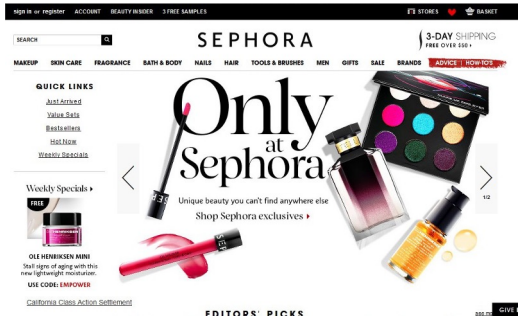

- Step 3) Hypothesis Testing and Interpretation
  - Note: A/B Test = Hypothesis Test
  - What is statistically significant for our test of our hypothesis?
  - Do we go with product feature A or B?

# Back to Sephora: Webpage A vs Webpage B (now with A/B test)

- Now Sephora ran Webpages A and B
  - Users randomly assigned A or B
- Outcome
  - Webpage A: 10% click-through-rate
  - Webpage B: 12% click-through-rate




Old Webpage A




New Webpage B

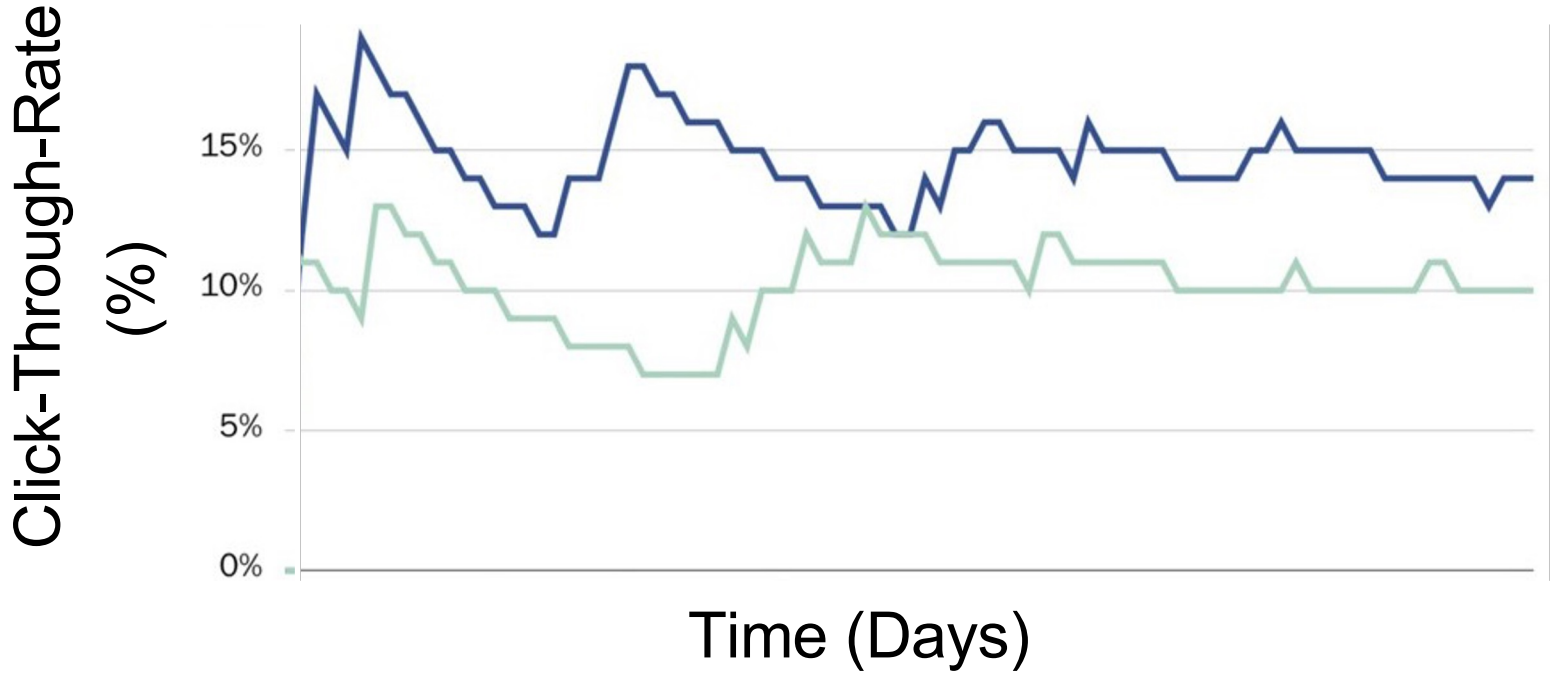
- Question: Do we implement Webpage B? Why or why not?
- Answer: Not yet! We don't know if this is statistically significant.

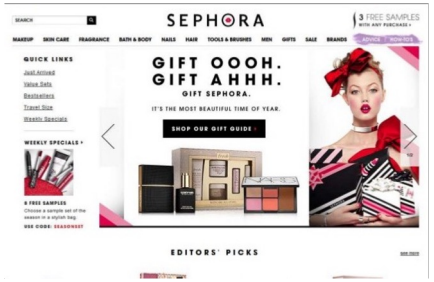
| Webpage | Number of Samples | Click-Through-Rate |
|---|---|---|
| A | 1000 | 10% |
| B | 1000 | 12% |

# WHY HYPOTHESIS TEST?

# ANSWER: BECAUSE A AND B HAVE RANDOMNESS.

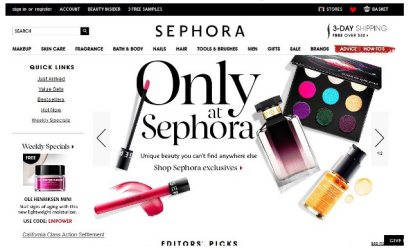
# WE NEED TO DETECT SIGNAL OVER NOISE




Webpage A

Webpage B




Notice: a lot of “bouncing around” of metric for A and B.

# KEY POINT: METRICS NEARLY ALWAYS HAVE UNEXPLAINABLE RANDOMNESS.

# WE NEED (STATISTICAL) HYPOTHESIS TESTING TO CHECK SIGNIFICANCE.

- Why randomness?
  - We do not observe all reasons why people are bouncing at our webpage
  - Example: Economy bouncing back, Valentines Day sales for make up
- Common mistake
  - This is not "measurement error," our measurements are fine
- Statistical Randomness of Sample vs Population
  - The data we collected are only samples of overall population.
  - We don't know if we got samples that randomly had more click-through-rate in general.
  - We need statistics to help account for this.

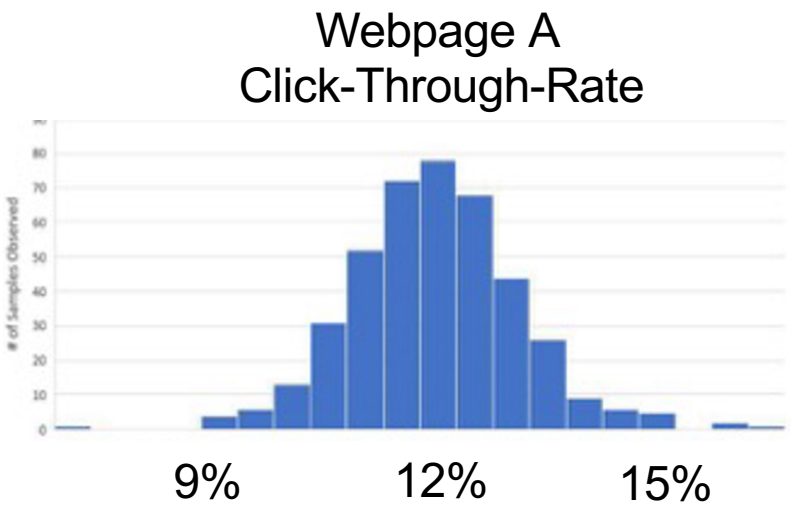
| Webpage | Number of Samples | Click-Through-Rate |
|---|---|---|
| A | 1000 | 10% |
| B | 1000 | 12% |

Click-Through-Rate (CTR) over Time


12% +/- 3% Click Through Rate

# HYPOTHESIS TESTING CONCEPTS

- *Null hypothesis*
  - *The hypothesis, often referred to as $H_0$, that A and B are not different and observed differences during experiment are due to random fluctuations.*
- *P-value*
- *Confidence level.*
  - *The probability of failing to reject (i.e., retaining) the null hypothesis when it is true.*
  - *Confidence level.* Commonly set to 95%, this implies that 5% of the time we will incorrectly conclude that there is a difference when there is none (Type I error). All else being equal, increasing level reduces our statistical power.
- *Alpha or Significance Level*
  - 1 – Confidence Level
  - There is a 95% chance of the new feature beating the original feature
- *Statistical Power*
  - *The probability of correctly rejecting the null hypothesis, H0, when it is false. Power measures our ability to detect a difference when it indeed exists.*
- *Standard error*
  - SD of the sampling distribution; The smaller the Std-Err, the more powerful the test.




| Reality | Measured: Do not reject $H_0$ | Measured: Reject $H_0$ |
|---|---|---|
| $H_0$ is true | Correct decision ☺ | Type I False Positive (α) |
| $H_0$ is false | Type II False Negative (β) | Correct decision ☺ |

# NULL HYPOTHESIS: EXAMPLE OF RESTAURANT TECH PRODUCT FEATURE

Hypothesis definition for product feature

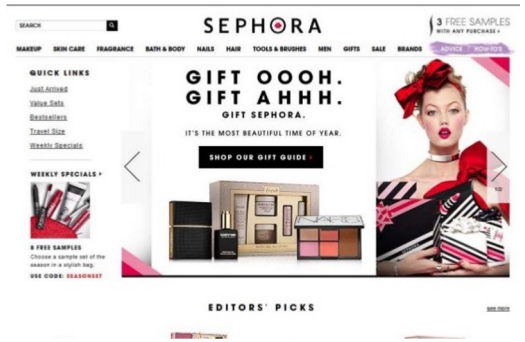
"[Specific repeatable action] will create [expected, measurable result]"

Example: "Restaurants that add the food pickup feature will increase their overall number of orders per day"

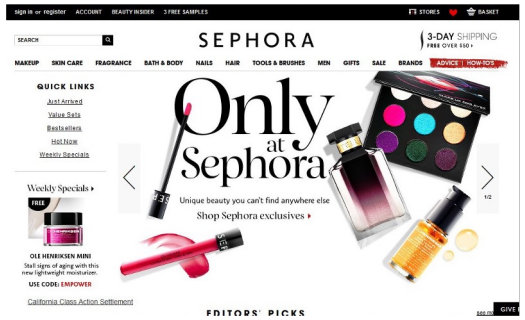
- $H_0$ *(null)*: Restaurants that add the food pickup feature will neither increase or decrease total number of orders per day
- $H_1$ *(ours)*: Restaurants that add the food pickup feature will increase their overall number of orders per day

# QUESTION: WHAT IS NULL HYPOTHESIS AND HYPOTHESIS TO TEST?

Context: Testing two version of website – A (old) and B (new)
Metric: Click-through-rate (CT) for header banner on website



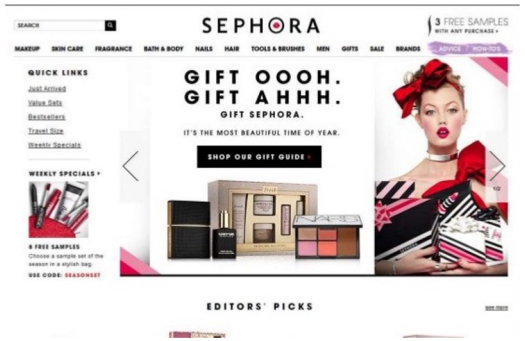

A



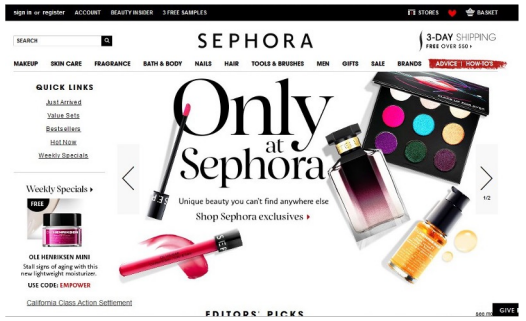

B

- $H_0$: <null hypothesis>
- $H_1$: <hypothesis to test>

# ANSWER: WHAT IS NULL HYPOTHESIS AND OUR HYPOTHESIS?



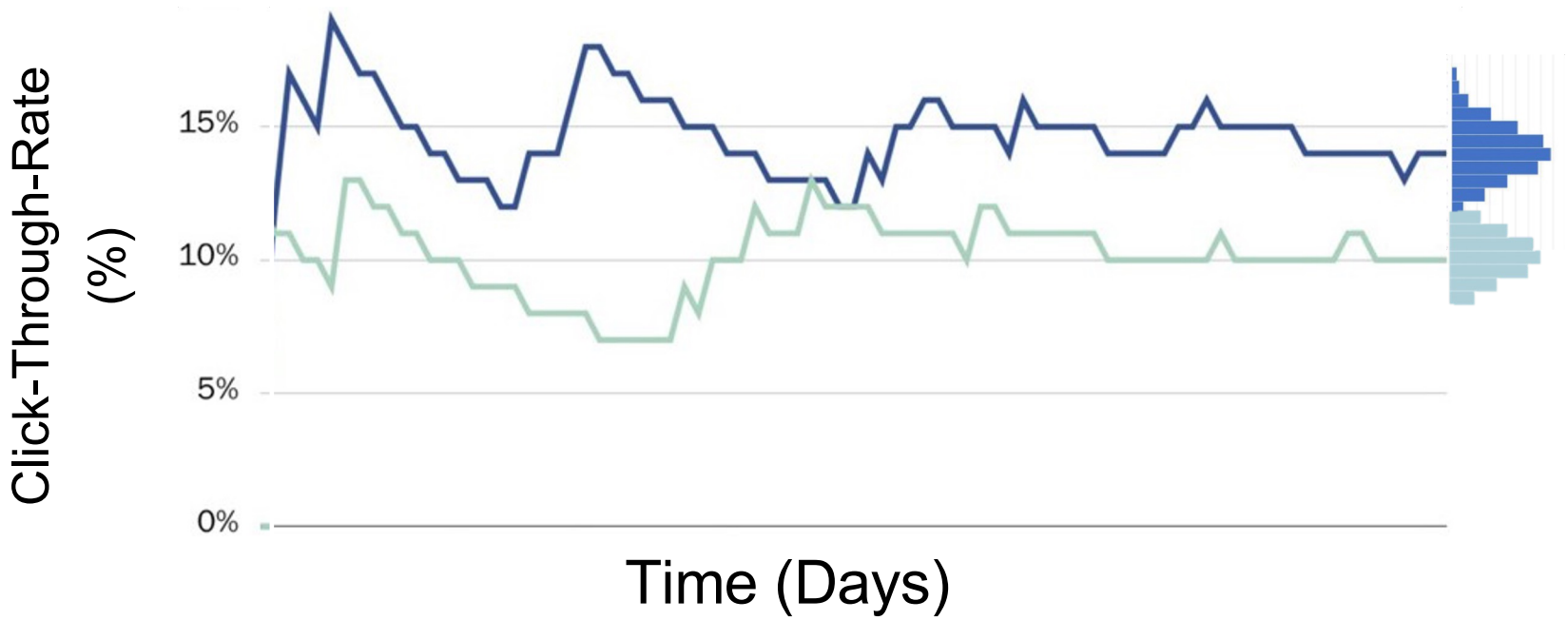

A

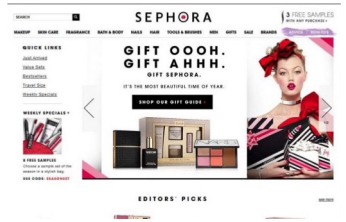



B

- $H_0$: the click through rate is the same for A and B.
- $H_1$: the click-through-rate is higher (or lower) for webpage A than webpage B. There is an "effect."

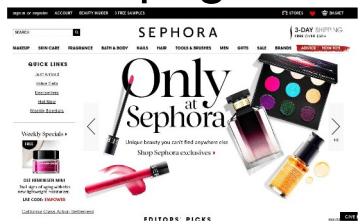
# INTUITION: "IS B BETTER THAN A?" AND THEIR DISTRIBUTIONS




Webpage A

Webpage B



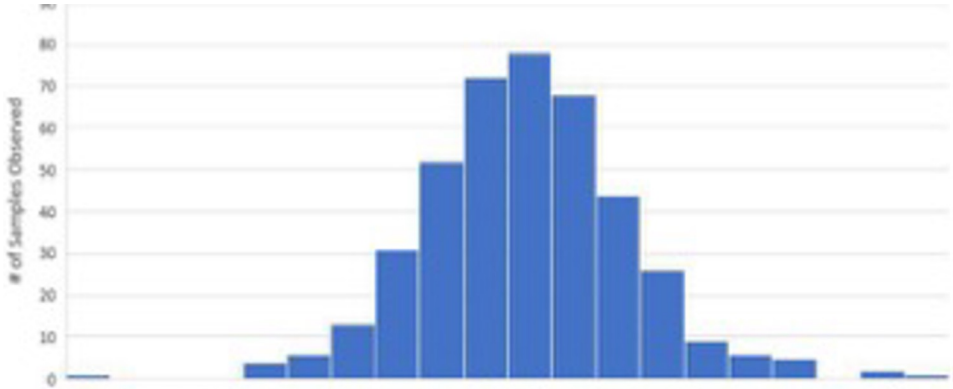

Notice: There is a lot of "bouncing around" of metric for A and B.

Key Point: This randomness leads to a distribution of our tracked metric for A and B (blue and teal distributions).

# Intuition: The "normal" distribution of A and B

- "Normal" is the "statistical model" we will be using for click-through-rates (and A/B testing)
  - A.k.a., the "Gaussian" Distribution
- Technical Note:
  - We actually need "Binomial Distribution" - the number of Heads in a sequence of Bernoulli Trials with replacement
  - But this is approximated with a Gaussian

Webpage A
Click-Through-Rate

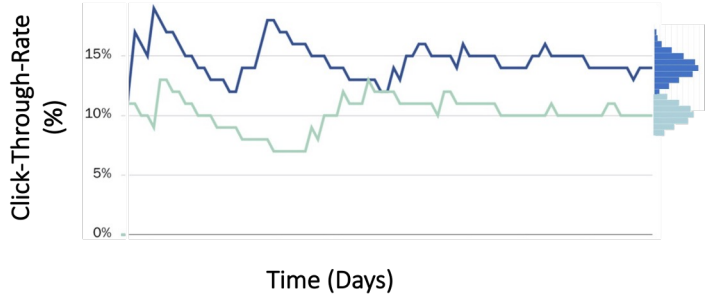



9% 12% 15%

# Intuition for hypothesis test: overlapping distributions A and B

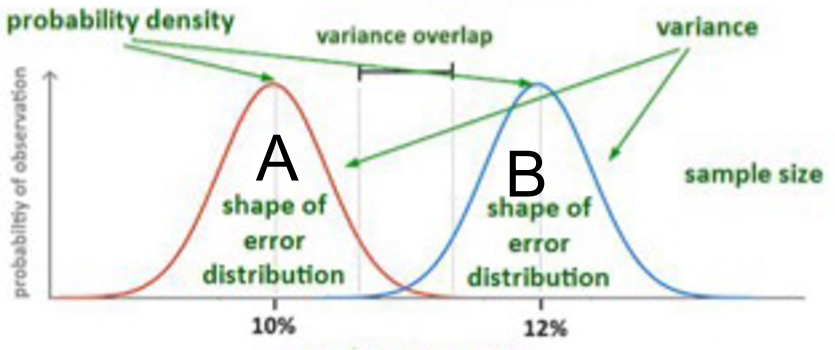
## Overlap of Two Distributions

- Webpage A and Webpage B



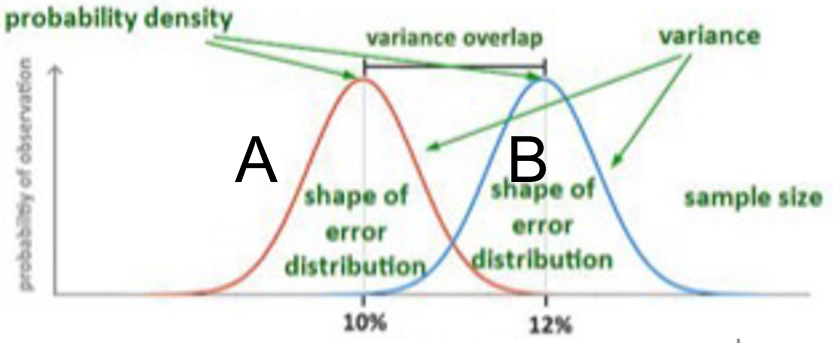

## Intuition: Less overlap of A and B

- <u>More likely</u> an “effect” of Webpage B versus A
- “Webpage B increases click-through-rate (CTR)”



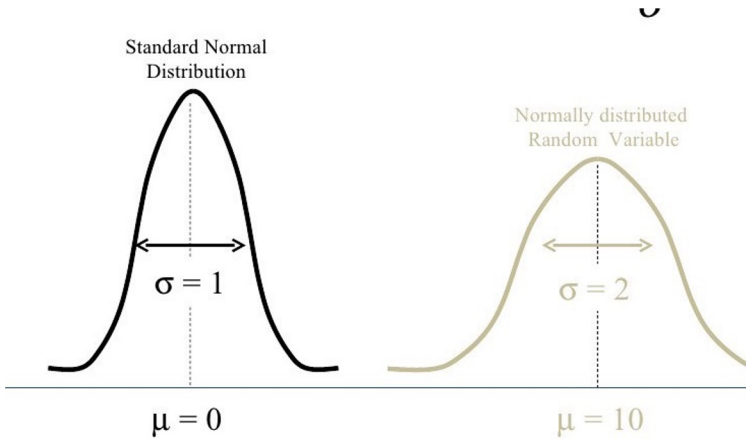

## Intuition: More overlap of A and B

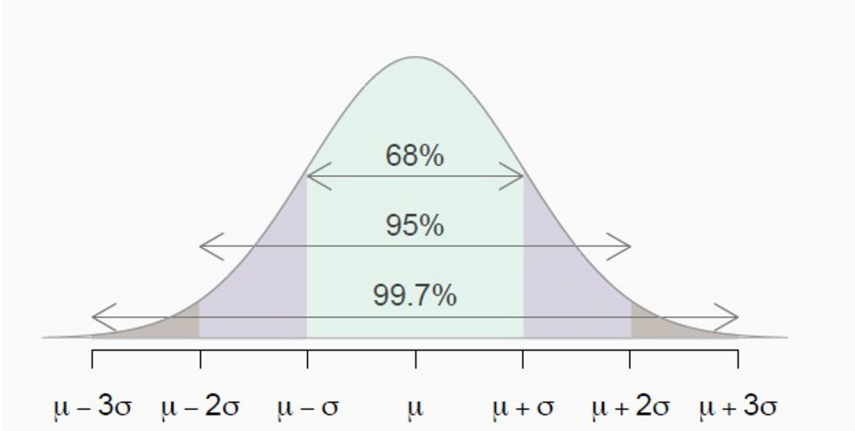
- <u>Less likely</u> there is an “effect” of B vs A
- “Webpage B doesn’t change CTR”



# How to hypothesis test: converting data from A and B

- Data on A and B
  - Users that saw either Webpage A or Webpage B
  - "Distribution" of user data for each webpage
- Take the difference between webpage A and B distributions.
  - This creates a new distribution which we can convert to a "standard" Normal distribution
- Statistical Test
  - This allows us to use a "Z-Test" to test our hypotheses

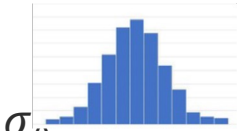


# How to hypotheses test:

## Mean and Standard Deviation of Collected Data

- Webpage A:
  - Mean $\mu_A$
  - Standard Deviation: $\sigma_A$
  - Data sample $i$ of CTR: $a_i$
  - Sample Size: $n_A$



- Webpage B:
  - Mean $\mu_B$
  - Standard Deviation: $\sigma_B$
  - Data sample $i$ of CTR: $b_i$
  - Sample Size: $n_B$

- Z-Statistic
  - Difference of Means
  - Scale by Standard Deviations

Mean and Standard Deviation of Webpage A and Webpage B

$$\hat{\mu}_A = \frac{1}{n_A}\sum_i a_i \text{ and } \hat{\sigma}_A = \frac{1}{n_A}\sum_i (\hat{\mu}_A - a_i)^2$$

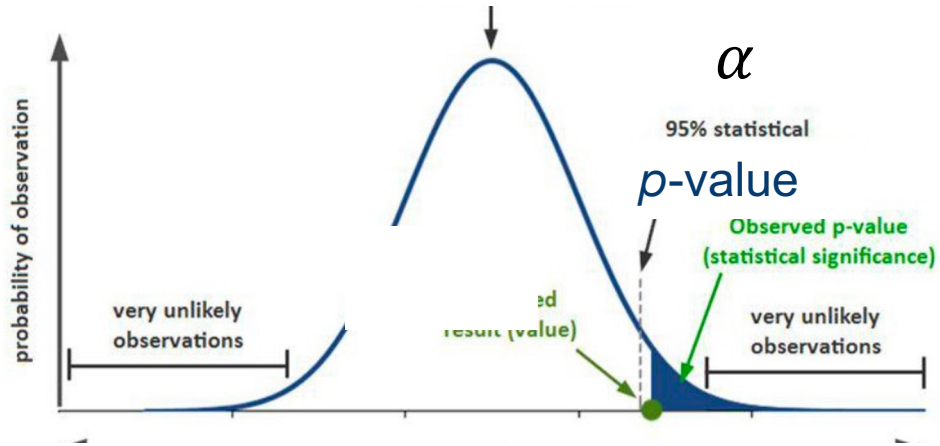
$$\hat{\mu}_B = \frac{1}{n_B}\sum_i b_i \text{ and } \hat{\sigma}_B = \frac{1}{n_B}\sum_i (\hat{\mu}_B - b_i)^2$$

"Z-Transformation of our Data"
(Difference between Webpage A and B)

$$z_{AB} = \frac{\hat{\mu}_B - \hat{\mu}_A}{\sqrt{\frac{\hat{\sigma}_B^2}{n_B} + \frac{\hat{\sigma}_A^2}{n_A}}}$$

# STATISTICAL SIGNIFICANCE

- How?
  - Choose significance level $\alpha$ for rejecting the null hypothesis $H_0$ that webpage A and B have same CTR




- Reject $H_0$ if our *p*-value is **<= *a***
  - This means we find H1 true
  - Or more accurately, H1 is more consistent with the data

- H0: “the click through rate is the same for the two webpages”
- H1: “the click-through-rate is higher (or lower) for webpage B than A

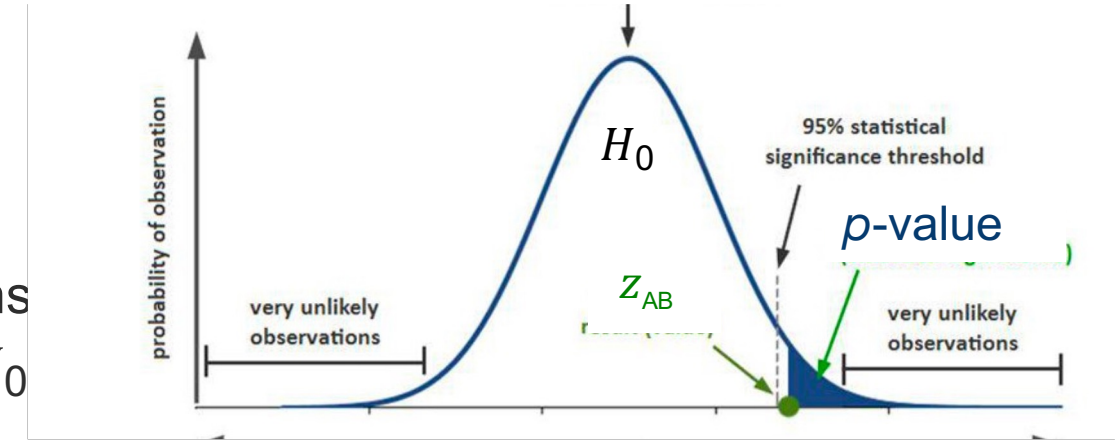
# *P*-VALUE

- *p*-value – Measure of the strength of evidence the sample data provides against the null hypothesis $H_0$
  - We get *p*-value from z-statistic $z_{AB}$

$$p\text{-value} = P(Z \geq z_{AB};\ H_0)$$

- *p*-value is the probability of the null hypothesis $H_0$ giving a more extreme difference between webpage A and B than the observed difference $z_{AB}$

- It's the amount of "tail" in the difference of means distribution, the standard Normal specified for $H_0$

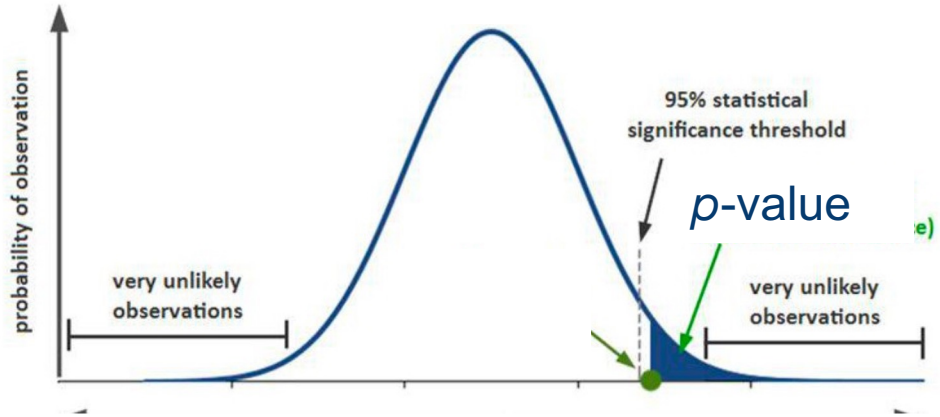


# STATISTICAL SIGNIFICANCE: COMPARING *P*-VALUE WITH ALPHA

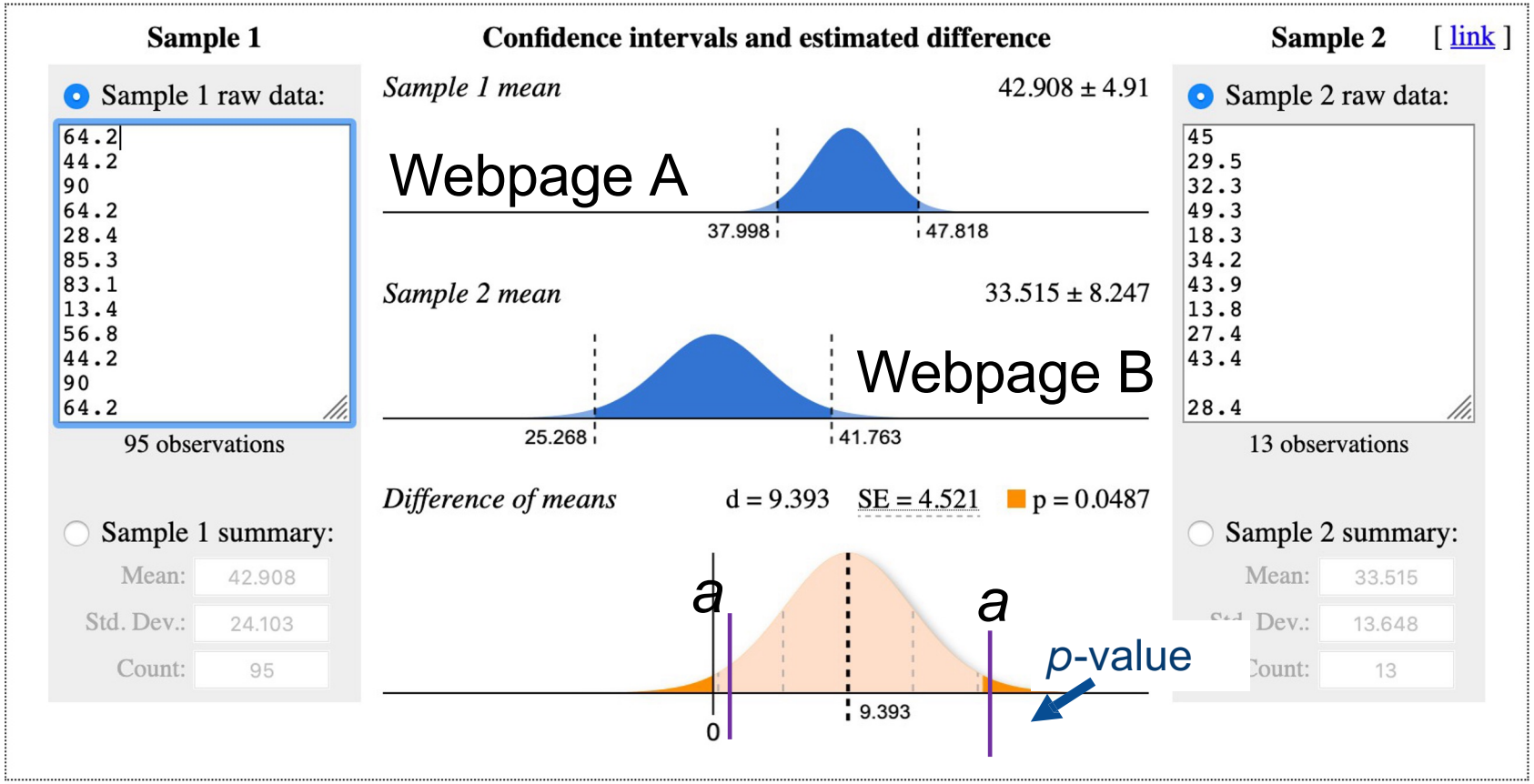
- We saw comparing p-value to alpha performs hypothesis test. But how do we interpret?

- *p*-value: We do not choose this. This is calculated from data.

- Alpha or "Significance Level"
  - We choose this. Default a is often 5%
  - You may have heard, "$p < 0.05$"
  - There is a 5% or less chance of "false positive'
  - There is a 95% chance of the new webpage A having higher CTR than the old webpage B. This interpretation is called the "confidence level"



# STATISTICAL SIGNIFICANCE: OVERLAPPING DISTRIBUTIONS




*Verdict:* Sample 1 mean is greater

Webpage A is statistically significant in its CTR from Webpage B

# QUESTION: DOES P-VALUE < 0.05 ALWAYS MEAN STATISTICALLY SIGNIFICANT?

- We choose the alpha. It just happens that many academic fields have adopted alpha of 0.05
  - This was introduced in 1925
  - It is an arbitrary choice.
  - Physicists for example used a p-value of 0.0000003 for the Higgs Boson

- p < 0.05 is very abused
  - With "internet scale" data, we can often "find" statistical significance.

Title: Redefine Statistical Significance

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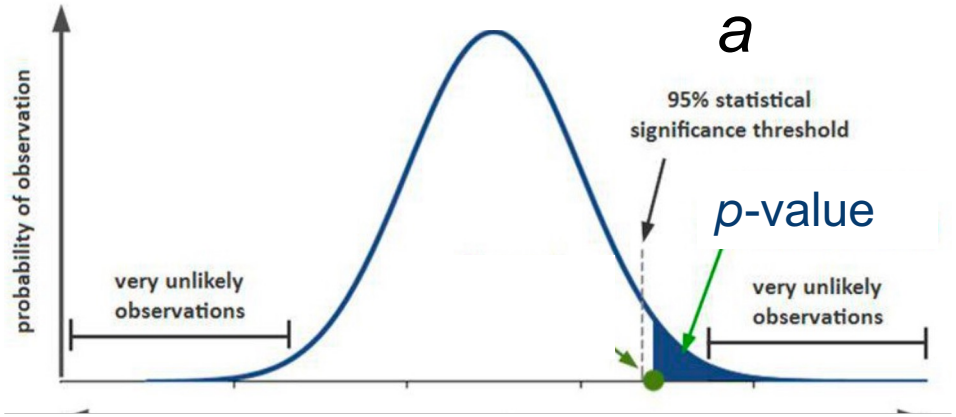
# QUESTION: WHAT CAN LEAD TO A LOW P-VALUE?

Observing a low *p*-value means either:

1. The null hypothesis is not true.
2. The null hypothesis is true, but we have observed a very rare outcome
3. The statistical model is inadequate so the calculated *p*-value is not an actual *p*-value.

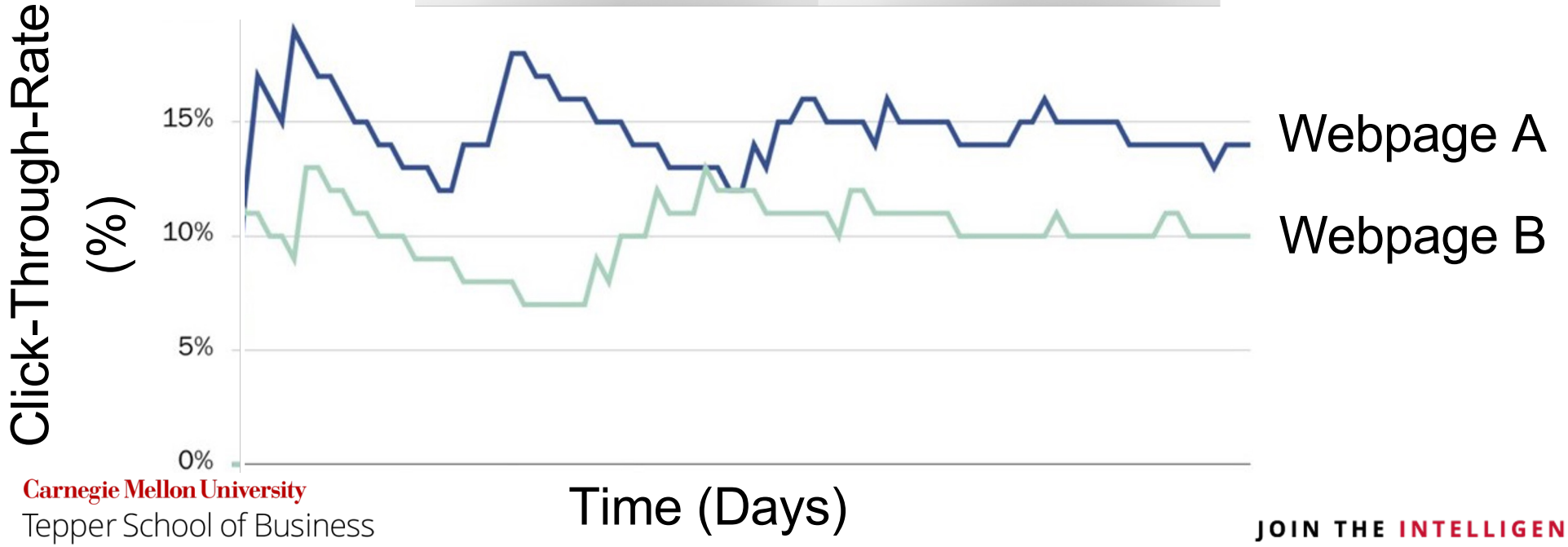


# How to get a low p-value

- The larger the variance of the data, the larger the p-value, all else being equal.
- The larger the sample size, the smaller p-value, all else being equal.
- The larger the observed discrepancy, the smaller the p-value, all else being equal.

Recommended interactive visualization of how sample size and variance affect statistical significance: https://www.evanmiller.org/ab-testing/t-test.html

# QUESTION: HOW LONG SHOULD WE RUN A/B TEST?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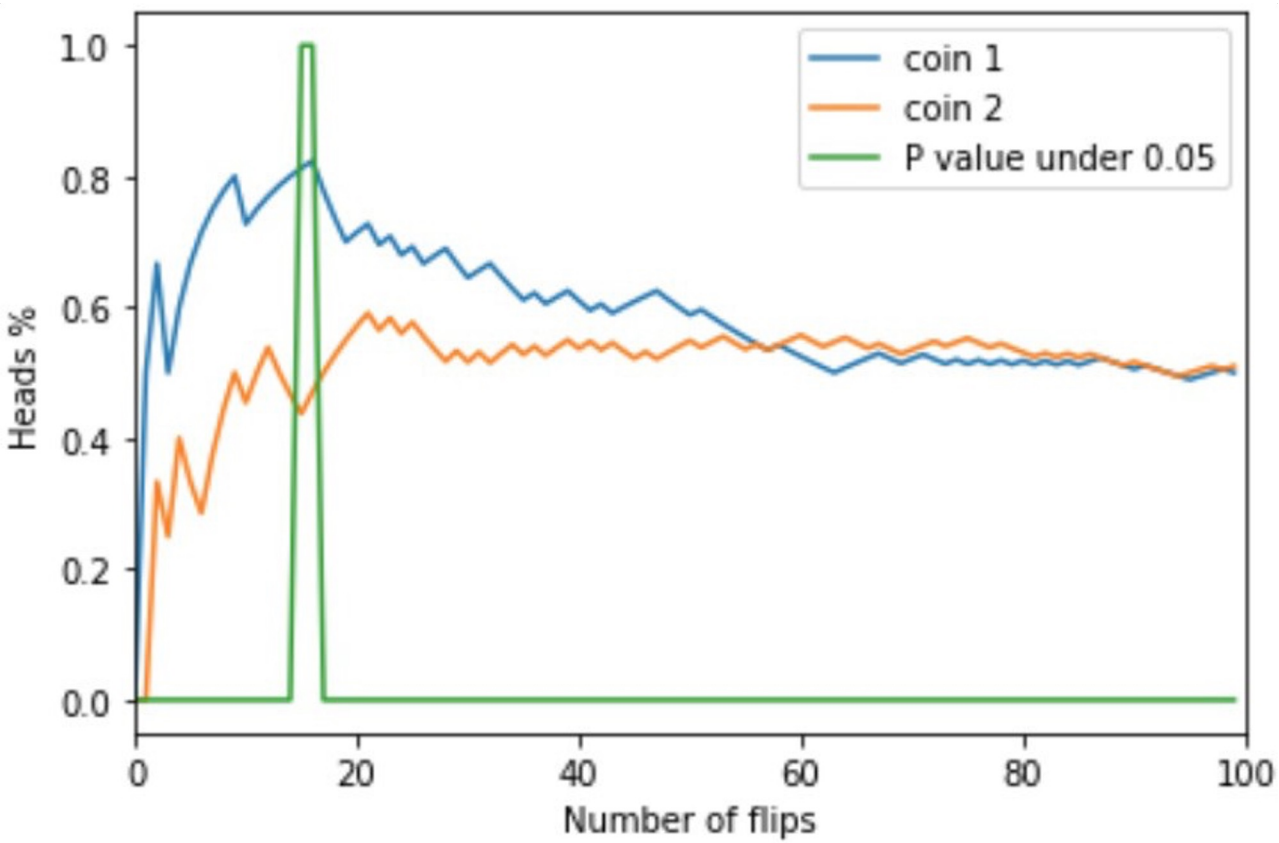
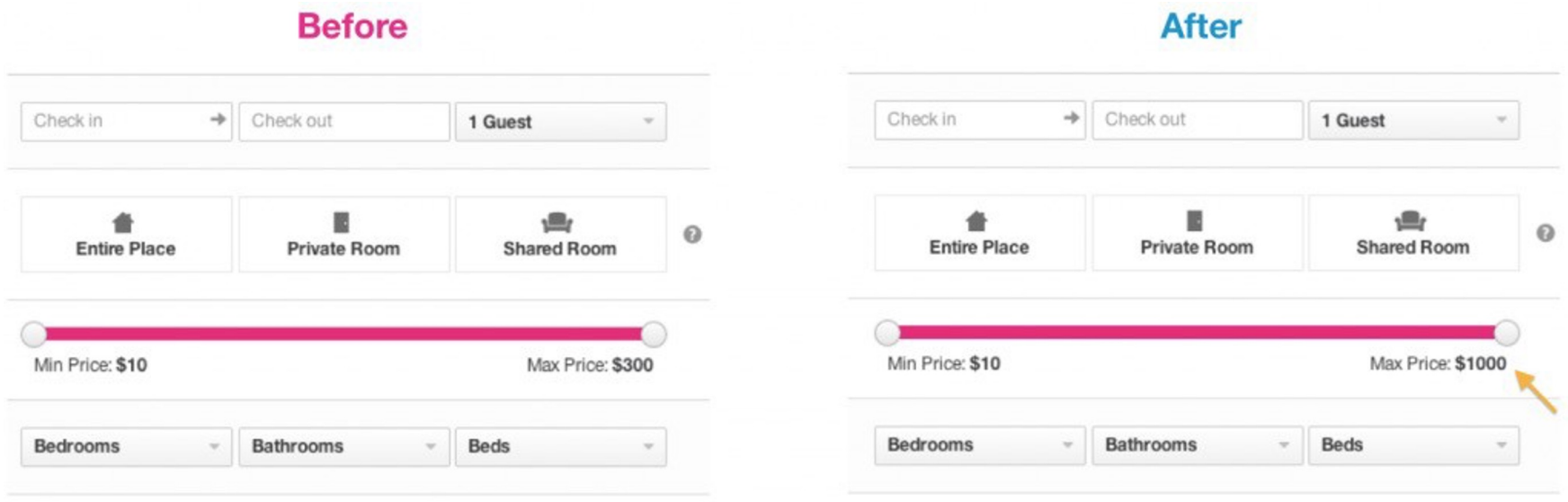
# COMMON PITFALL: EARLY STOPPING

- Imagine two coins
  - Coin 1: 50% Heads
  - Coin 2: 50% Heads

- "If we stopped when we saw a "significant effect" we would have said the 2 coins were different



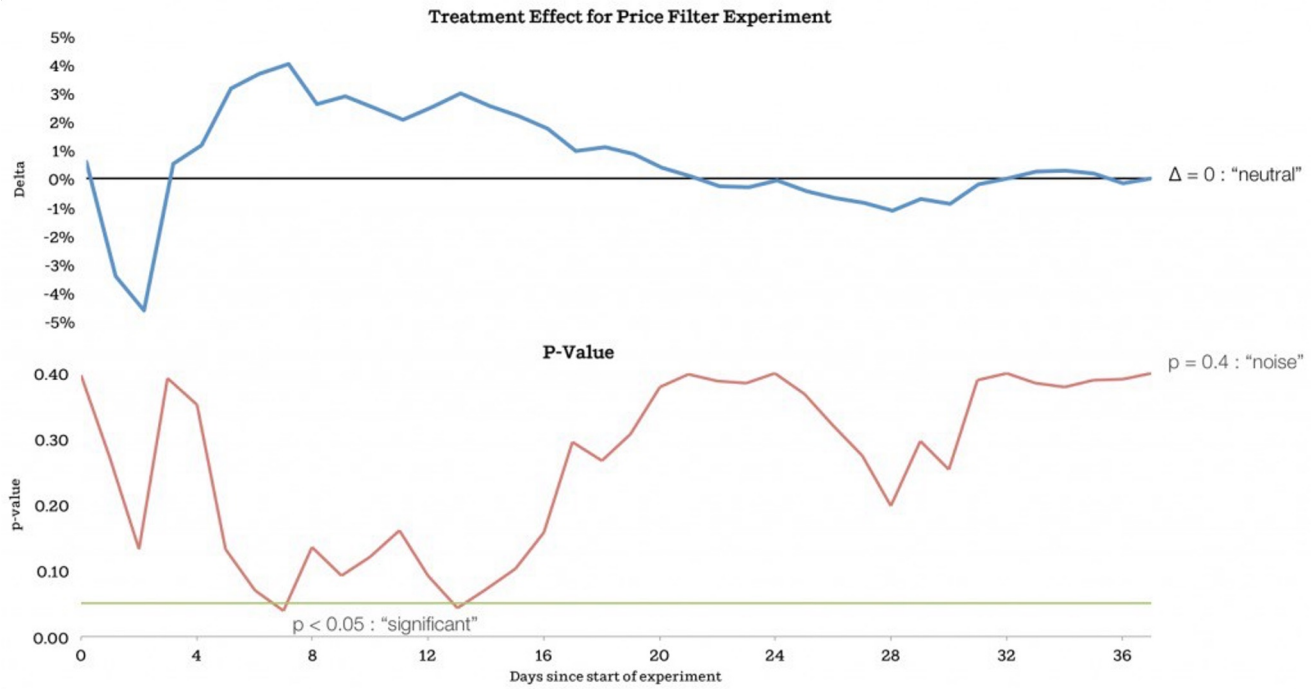
# REAL EXAMPLE: AIRBNB




- Changing the Maximum Price Filter on Search Page

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

# REAL EXAMPLE: AIRBNB




Takeaway: If Airbnb stopped when it was "significant" then this would have been (an incorrect) spurious correlation.

# TODAY'S LEARNING OBJECTIVES

- Motivating Example: Compare.com
- What and Why A/B Test?
  - Focus on Intuition and Definitions
  - 3 Steps for A/B Testing
- How to A/B Test?
  - Statistical Significance
  - Concepts: p-values, confidence intervals, etc.