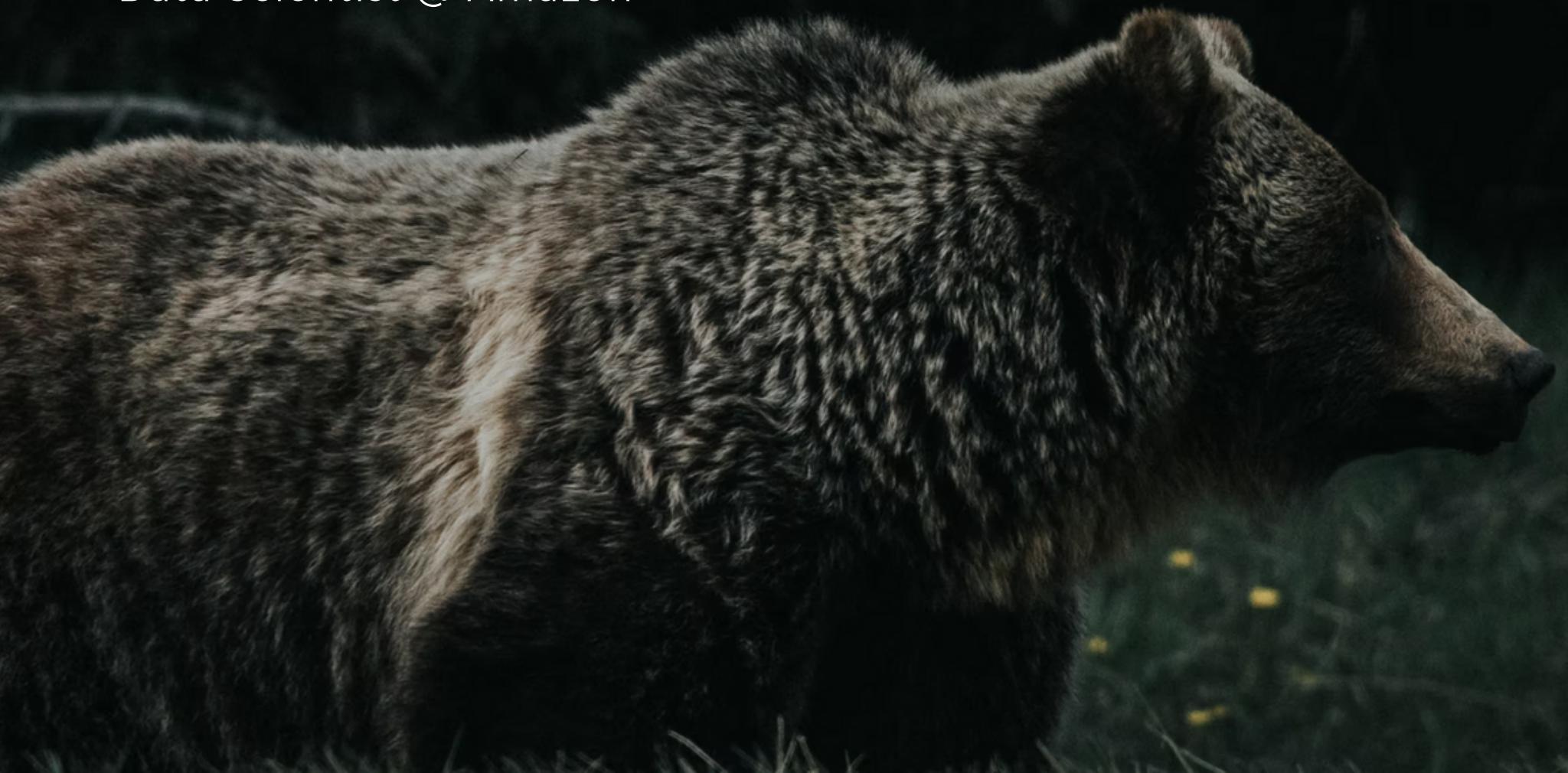


A/B Testing in the Wild

How to Get Started

Charin Polpanumas

Data Scientist @ Amazon



Which Sunflower Seed Packet Will Sell Better?

Gut feeling - what does your instinct tell you?



Red Pack
(Current)



Grey Pack
(Experimental)

Hamster Inc. is a large food-and-beverage corporation operating in Hamland. One of its flagship products is sunflower seed packets. It is considering changing packaging color from red to grey.

How Business Decisions Are Made



- Realistic assumptions
 - Scientific methods
-
- Gut feelings
 - Extrapolation from past experiences
 - Proxies
 - Fear of missing out (FOMO)
 - Highest Paid Person's Opinion (HiPPO)



Randomness in Business Decisions

Customer preferences, trends and seasonality, competitors



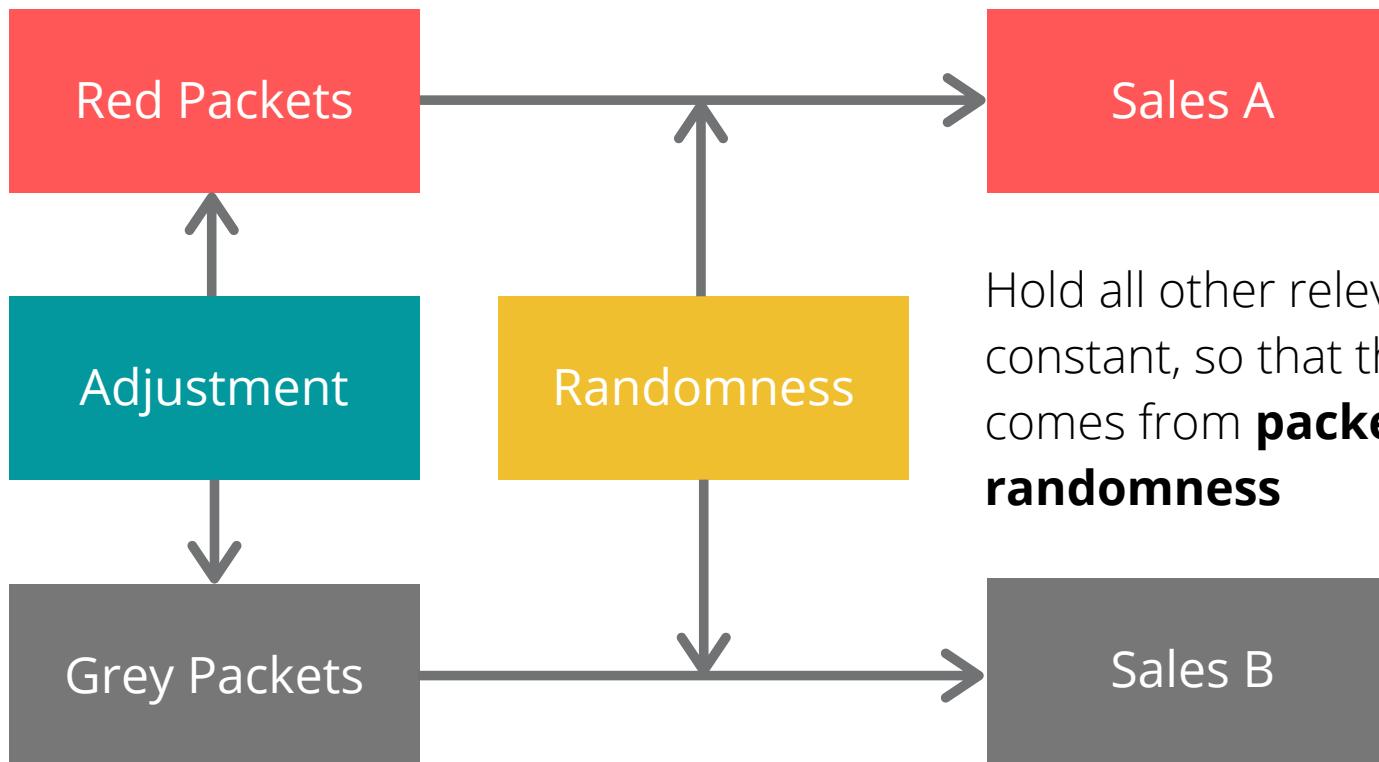
- Chess
- Go
- Checkers
- Santorini



- UI/UX improvements
- Marketing campaigns
- Product development
- Clinical trials

How to Deal with Randomness

Everything else being equal, what is the effect of actions on outcomes



Hold all other relevant factors constant, so that the only difference comes from **packet color** and **randomness**

A/B Test Use Case Montage

Who have done it? Was it worth it?



Bing Link Color Changes (2014)

Bing made 10M USD more from ads with a different link color

The figure consists of two side-by-side screenshots of the Bing search results page. Both screenshots show a search for 'amazon'.

Left Screenshot (Blue Links):

- Header: WEB, IMAGES, VIDEOS, MAPS, NEWS, MORE
- Search bar: amazon
- Results count: 202,000,000 RESULTS
- Time filter: Any time ▾
- Ad related to amazon:
 - [Amazon.com® Official Site - Huge Selection and Amazing Prices.](#)
 - www.Amazon.com - Official Site
 - Free Shipping on Orders Over \$25
 - Amazon Prime Prime Instant Video
 - Join Amazon Student Rent Textbooks
 - Download eTextbooks Kindle Store
- Organic search result:
 - [Amazon.com: Online Shopping for Electronics, Apparel, Computers ...](#)
 - www.amazon.com ▾ Official site
 - Customer service 866-216-1072
 - Online shopping from the earth's biggest selection of books, magazines, music, DVDs, videos, electronics, computers, software, apparel & accessories, shoes, jewelry ...
- Side navigation:
 - Books**
Shop online for millions of new and used books
 - Music**
Browse best sellers, new releases, deals, vinyl records, MP3s, and ...

Right Screenshot (Green Links):

- Header: WEB, IMAGES, VIDEOS, MAPS, NEWS, MORE
- Search bar: amazon
- Results count: 202,000,000 RESULTS
- Time filter: Any time ▾
- Ad related to amazon:
 - [Amazon.com® Official Site - Huge Selection and Amazing Prices.](#)
 - www.Amazon.com - Official Site
 - Free Shipping on Orders Over \$25
 - Amazon Prime Prime Instant Video
 - Join Amazon Student Rent Textbooks
 - Download eTextbooks Kindle Store
- Organic search result:
 - [Amazon.com: Online Shopping for Electronics, Apparel, Computers ...](#)
 - www.amazon.com ▾ Official site
 - Customer service 866-216-1072
 - Online shopping from the earth's biggest selection of books, magazines, music, DVDs, videos, electronics, computers, software, apparel & accessories, shoes, jewelry ...
- Side navigation:
 - Books**
Shop online for millions of new and used books
 - Music**
Browse best sellers, new releases, deals, vinyl records, MP3s, and ...

Figure 1: Font color experiment. Can you tell the difference?

Speed Matters for Google Web Search (2009)

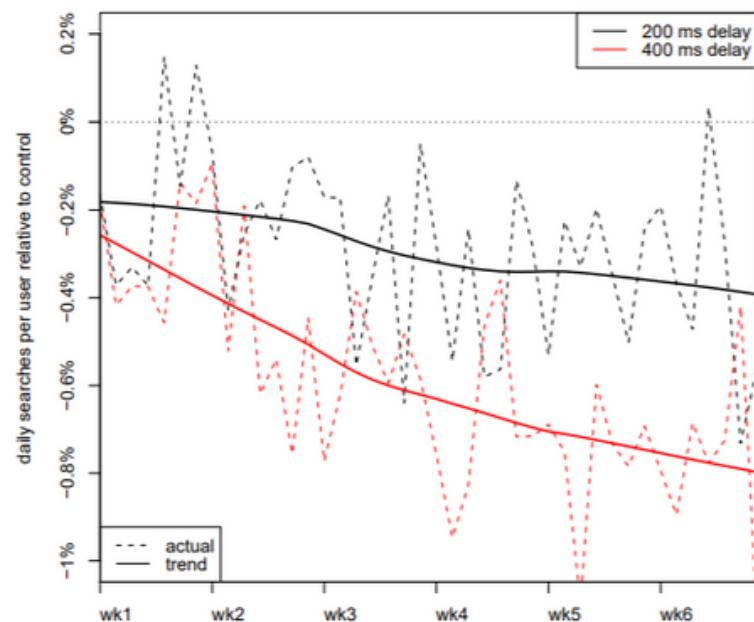
Longer website load time impacts daily usage per user

Table 1: Experiment Impact on Daily Searches Per User

Type of Delay	Magnitude	Duration	Impact
Pre-header	50 ms	4 weeks	—
Pre-header	100 ms	4 weeks	-0.20%
Post-header	200 ms	6 weeks	-0.29%
Post-header	400 ms	6 weeks	-0.59%
Post-ads	200 ms	4 weeks	-0.30%

Average impact over 4 or 6 weeks hides any trend over time. By focusing on the subset of users who were part of the experiment (or control group) from the beginning (as identified by a browser cookie), one can determine if there is such a trend. Figure 2 illustrates the trend for the two 6 week experiments.

Figure 2: Impact of Post-header Delays Over Time



A/B Shark Doo Doo Doo (2018)

In all, we have probably 30 or 40 different variations of Baby Shark

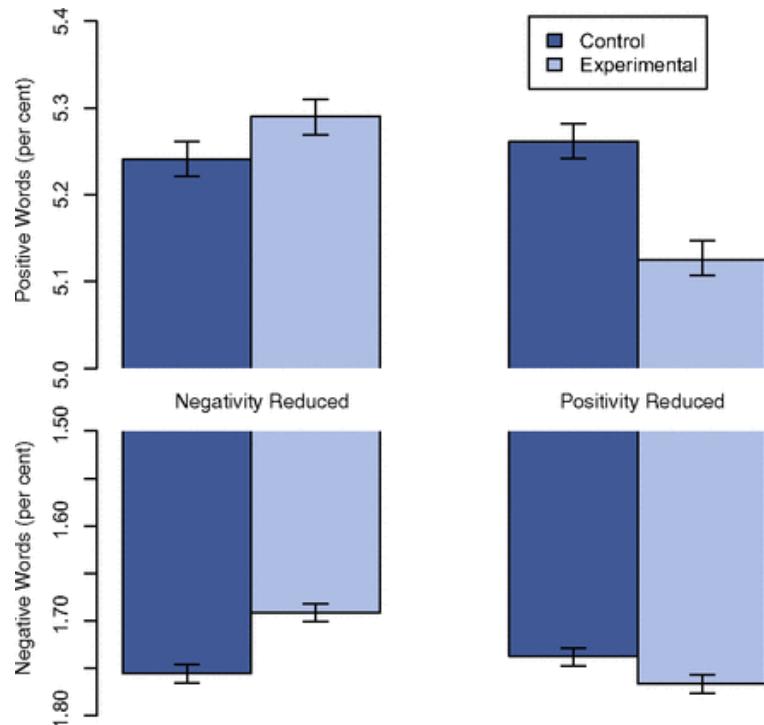


They have also re-recorded the song with different themed beats, including R&B and EDM versions. "In all, we have probably 30 or 40 different variations of Baby Shark,"

Jamie Oh
Pinkfong's global marketing director

Facebook Emotional Contagion Experiment (2014)

People will say more positive or negative things according to what they read



The experiment manipulated the extent to which people ($N = 689,003$) were exposed to emotional expressions in their News Feed. This tested whether exposure to emotions led people to change their own posting behaviors, in particular whether exposure to emotional content led people to post content that was consistent with the exposure.

Step-by-Step Guide to A/B Test in the Wild

1. Define relevant metrics
2. Split samples into comparable groups
3. Choose statistical tests and validate their assumptions
4. Decide on stopping criteria
5. Run and monitor the experiment
6. Analyze results and suggest actions

Which Sunflower Seed Packet Will Sell Better?

Why don't we A/B test it



เมล็ดทานตะวันอบรสพุตราจีน เม็ดใหญ่ สดใหม่ เคี้ยวเพลิน ขนาด 500 กรัม Sunflower Seed ตราอีสือเจีย

★★★★★ 28 Ratings

Brand: No Brand | More Chocolate, Snacks & Sweets from No Brand

฿50.00

฿70.00 -29%

Quantity

- 1 +

Buy Now

Add to Cart



www.hamzada.com/sunflower-seeds?variation=A



เมล็ดทานตะวันอบรสพุตราจีน เม็ดใหญ่ สดใหม่ เคี้ยวเพลิน ขนาด 500 กรัม Sunflower Seed ตราอีสือเจีย

★★★★★ 28 Ratings

Brand: No Brand | More Chocolate, Snacks & Sweets from No Brand

฿50.00

฿70.00 -29%

Quantity

- 1 +

Buy Now

Add to Cart

www.hamzada.com/sunflower-seeds?variation=B

Dr. Hamtarō Kamado decided to A/B test the packaging on hamzada.com—an e-commerce website. The goal is to find out which packet color customers **will more likely buy**.

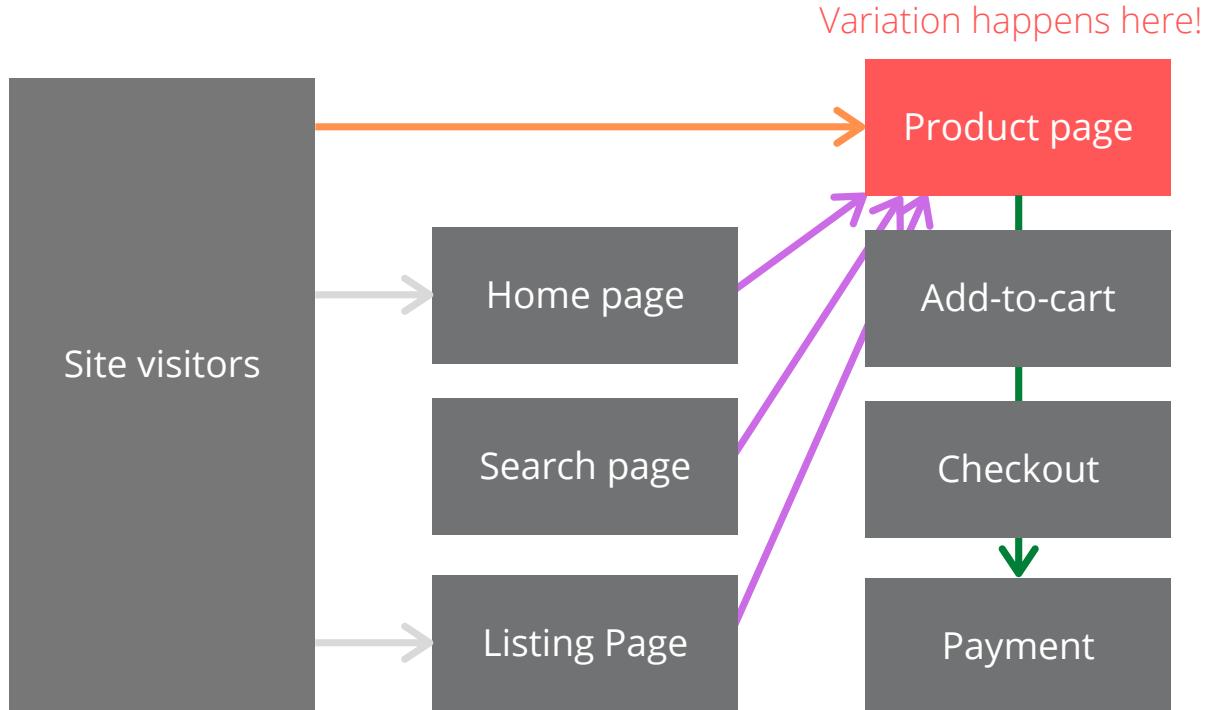
Define Relevant Metrics

Build intuition about your system

1. Relevance vs vanity
2. Granularity
3. Attribution periods
4. Assumed distributions
5. Robustness vs sensitivity
6. Features vs targets
7. Targets vs other targets

Relevance vs Vanity

Understand the context of the problem



Relevant metrics

1. conversions / conversion rates
2. add-to-carts / add-to-cart rates
3. checkouts / checkout rates

Vanity metrics

1. clicks / click through rates
2. product page views / visitors

Granularity

Most common metrics in A/B tests are event probabilities

Possible denominators

1. **Hits/Impressions** - number of times a page is viewed
2. **Sessions** - number of times the website is visited; timeout after 15-30 minutes
3. **Cookies** - number of cookies used to visit the website/page
4. **User Ids/Reach** - number of registered users who visited the website/page
5. **Device Ids** - number of devices who visited the website/page
6. **People** - number of actual people who visited the website/page

Possible event probabilities

1. **# checkout events / # hits** - double-count on page refreshes
2. **# checkout events/ # sessions** - double-count on inactive visits; good to see which products get bought within fewer visits
3. **# checkout events / # cookies on product page** - "users" as denominator; includes both logins and non-logins; different browsers/devices double-counts
4. **# payment events / # cookies on product page** - captures successful purchases
5. **# payment events / # user ids** - non-logins count as one user id
6. **# payment events / # people** - who are people?

Attribution Periods

Customer journey as denominator



payment events / # cookies per X day attribution

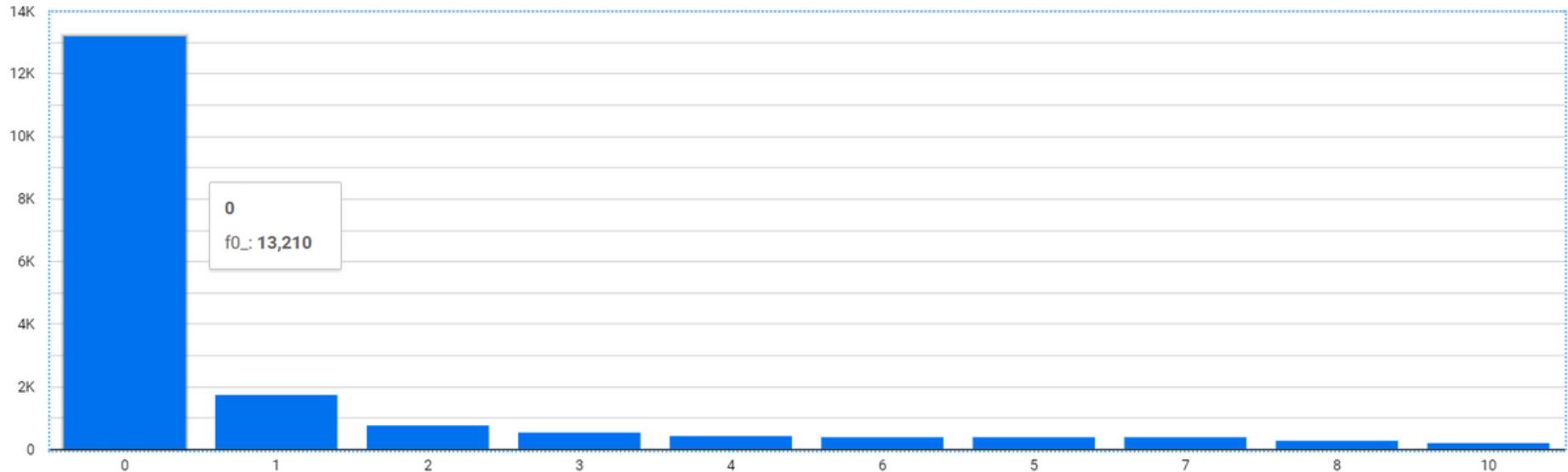
One-day attribution - 3 journeys; 1 success

Three-day attribution - 2 journeys; 1 success

One-week attribution - 1 journey; 1 success

Attribution Periods

How long is one customer journey? Plot it out!



Most people (cookies?) who visit e-commerce websites might end their journey in one day, whereas more complex sales might take weeks or months

Attribution Periods

Event-based vs cohort-based

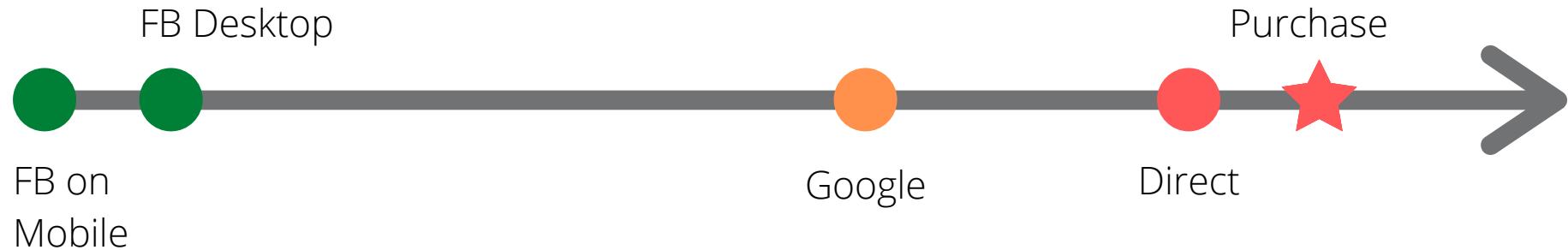
Conversion rate of August

conversions within August / number of users that visited in August

Conversion rate of August cohort

conversions within X days / number of users that visited in August

Example: Ads attribution



Assumed Distributions

Put the right assumptions on the right data

Frequentist hypothesis testing requires us to know the variance of the data.

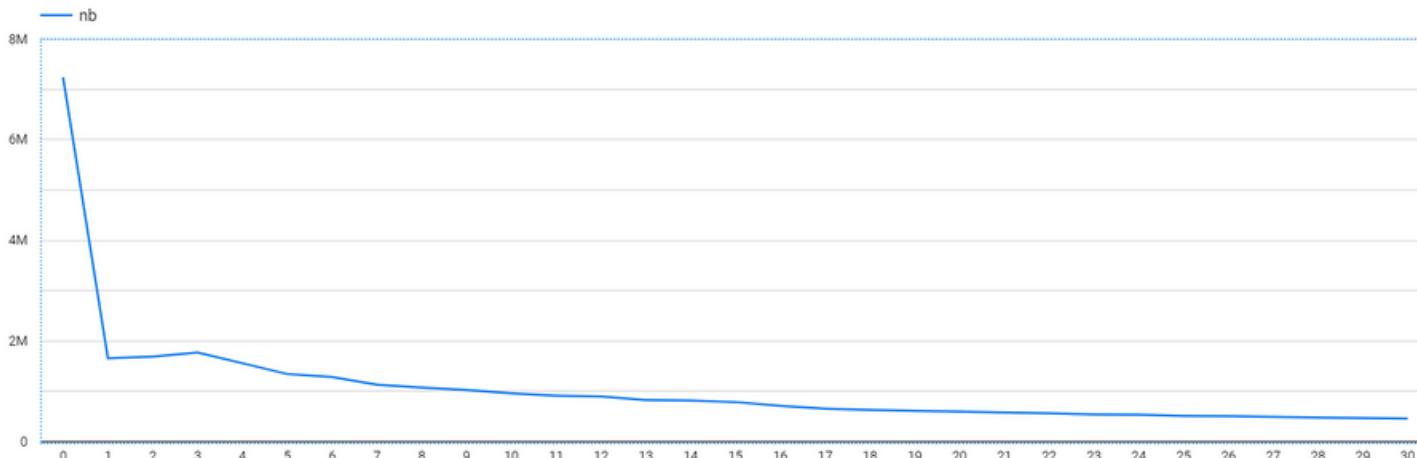
We typically assume the following distributions for the following data:

1. **Bernoulli** - event probability
2. **Exponential** - average revenue per user, average position clicked
3. **Normal/Student t** - height, weight, test scores, measurement errors

Also they ~~must~~ should be independent and identically distributed

How can we be sure? Plot it out!

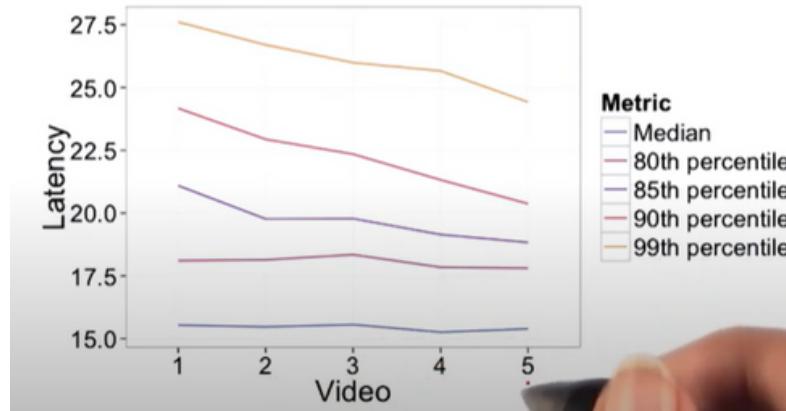
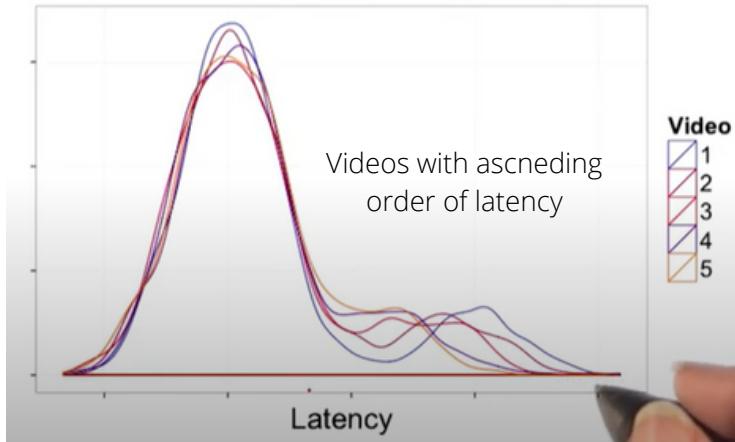
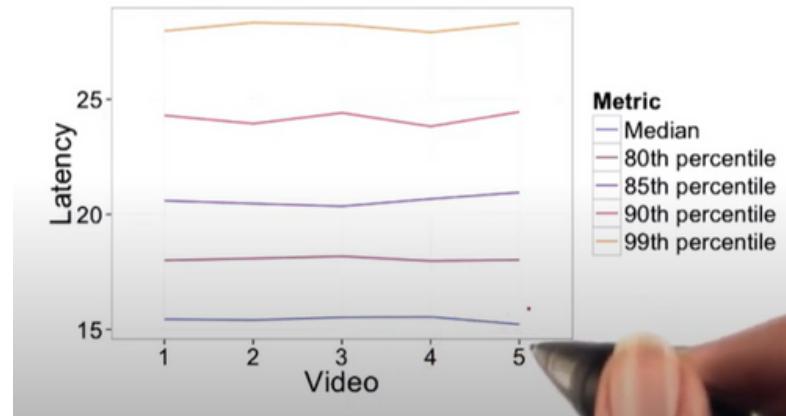
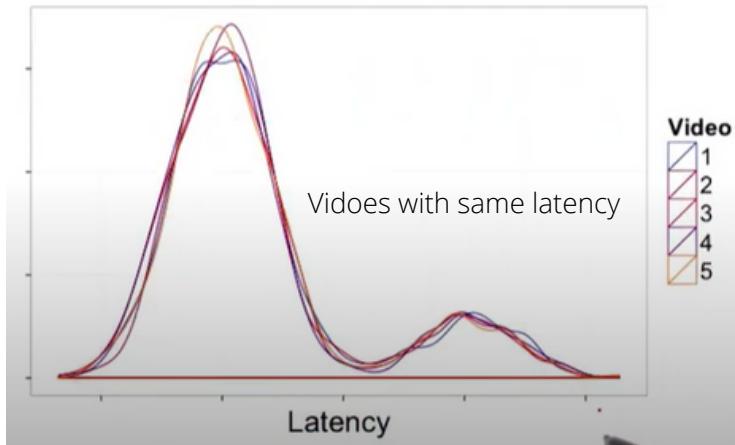
Example: average position clicked from listing page



Robustness vs Sensitivity

When you need to choose summary statistics to test

Example: summary statistics to represent YouTube video latency



Features vs Targets

Sometimes you train on one thing and optimize for the other

Problem: search re-ranking models that are trained on product clicks (since clicks are less sparse than conversions) make conversion rate worse

variant	#session	CTR	CR
original	3,322	43.86%	10.84%
model	3,281	43.68%	10.12%

Solution: makes product clicks count as 1 and conversions count as 2

variant	#session	CTR	CR
original	3,653	45.63%	13.09%
model	3,685	46.54%	14.11%

Targets vs Other Targets

Sometimes you need to decide on models trained on different targets

HAMZADA



Recommendation
for next purchase

Optimize for
**purchase within
session**

Inform about
member benefits

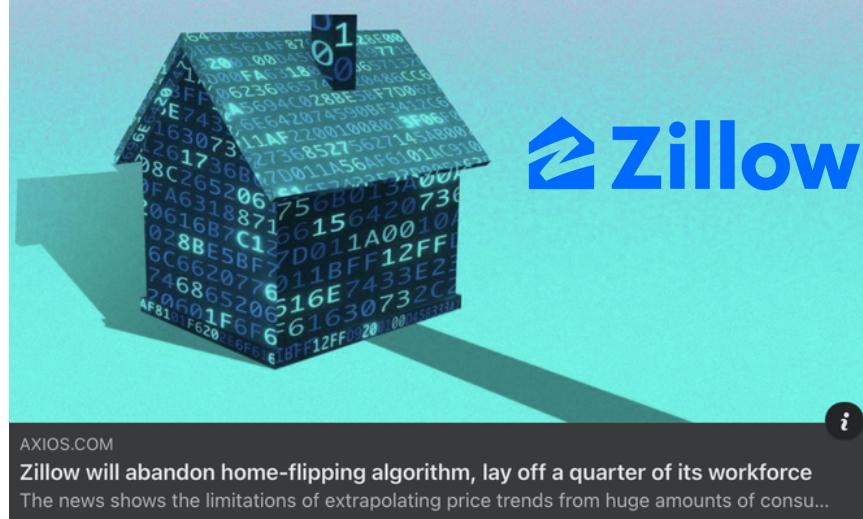
Optimize for
**retention in the
next month**

Recommendation for
next Father's Day

Optimize for
**purchase in the
next month**

Targets vs Other Targets

Synthetic targets; pros and cons



AXIOS.COM

Zillow will abandon home-flipping algorithm, lay off a quarter of its workforce
The news shows the limitations of extrapolating price trends from huge amounts of consu...

Create synthetic target metric, usually based on ML models. For example, create a model to predict one-month revenue based today's actions, then use that model to estimate the value of that action based on discounted version of that prediction.

Zillow abandons its home-flipping algorithm.
Model performs well with historical data, but homeowners noticed overpricing.

I'm from Zillow. Worked on algos. As another said, they were solid, well researched and performed well. Leadership stamped over the outputs with 'intuition' and that accounted for nearly all of the loss. It was easier to say the model failed than leadership, but we have the logs to prove otherwise.

2h · 47 Likes · Reply

...

Sunflower Seeds Packet A/B Test

Design journal



www.hamzada.com/sunflower-seeds?variation=A



www.hamzada.com/sunflower-seeds?variation=B

1. Metric - # payment / # cookie-days; each cookie is a Bernoulli trial (or the metric follows normalized binomial distribution)

Split Samples into Comparable Groups

Build intuition about your system

1. Split independently
2. Control for X
3. Frame the experiment fairly
4. Multiple experiments

Split Independently

Hypothesis tests rely on independent and identically distributed data

- If you are splitting on a larger granularity than what you are measuring, for example splitting on cookies while measuring at hit level, you will need more samples for the test to have the same power
 - **Hits** - measure usability; for example, does UI change make people more likely to click; might change on refresh
 - **Sessions** - measure usability but doesn't change within session
 - **Cookies** - same "users" always get the same results; for example, testing 2 recommendation models; changes only when browsers/devices change
 - **User Ids** - more strict than 3. but does not work on non-logins
- Hits and sessions are likely to be NOT independent since the same users can be recorded for both control and test groups
- Avoid making your groups interact with one another; for example, if you are testing out a new function on social media, avoid doing it with users who can interact with one another.

Split Independently

How adventurous is your team



50/50

Shorter time
Higher risks

80/20

Longer time
Lower risks

Control for X

Simpson's paradox - control for confounders

Story 1: "The Bad / Bad / Good Drug"

	Control Group (no drug)		Treatment Group (took drug)		
	Heart Attack	No HA	Heart Attack	No HA	
Female	1	19	3	37	60
Male	12	28	8	12	60
Total	13	47	11	49	

5% (1/20) women in **control** group had heart attack

7.5 % (3/40) women in **treatment** group had heart attack

→ Drug is bad for women

30% (12/40) men in **control** group had heart attack

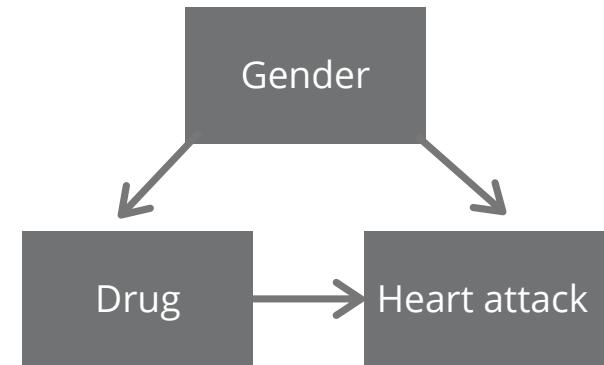
40% (8/20) men in **treatment** group had heart attack

→ Drug is bad for men

22% (13/60) **controls** had heart attack

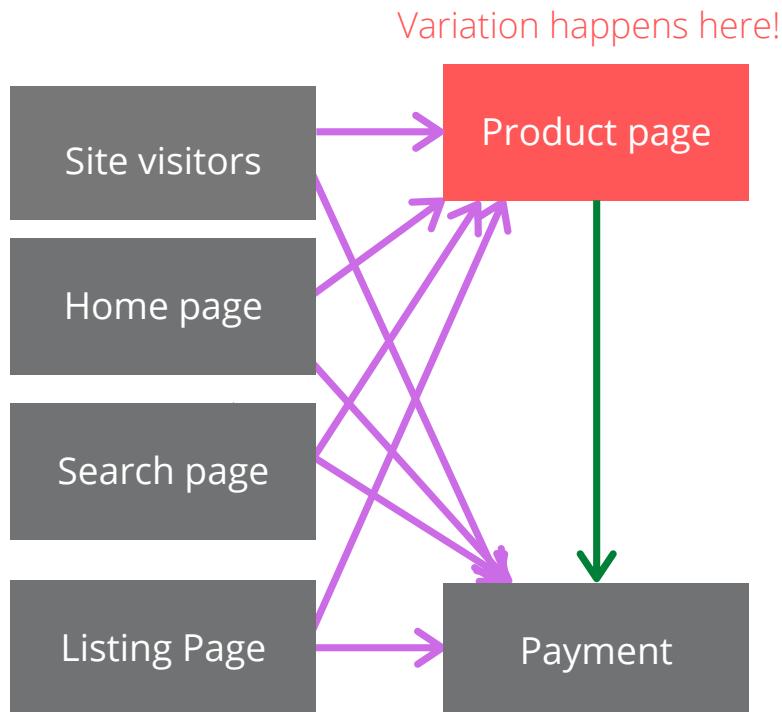
18% (11/60) **treatment** group had heart attack

→ Drug is good for people



Control for X

Simpson's paradox - control for confounders



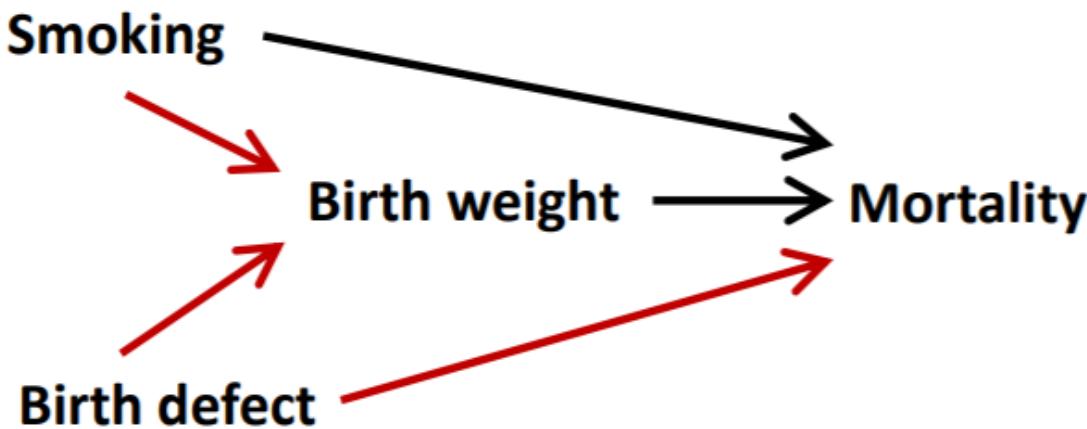
We can consider how the users come to product page as a confounder:

1. Search users might convert more easily because they are specifically looking for the sunflower seeds
2. Direct site visitors might convert less since they probably came from ads

(Do Not) Control for X

Smoking mothers - DO NOT control for colliders

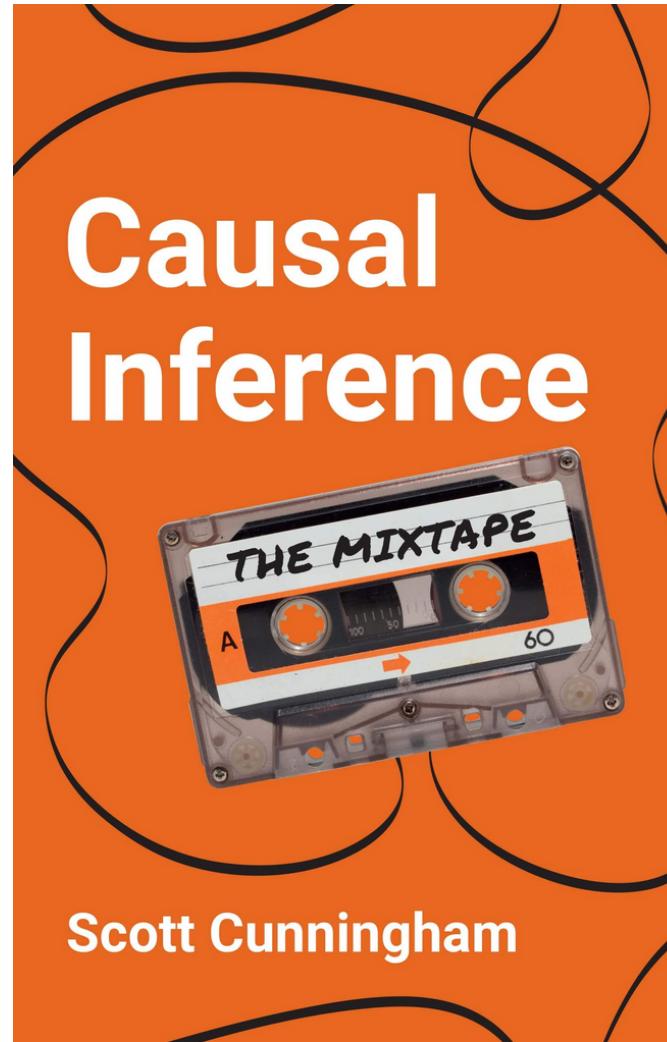
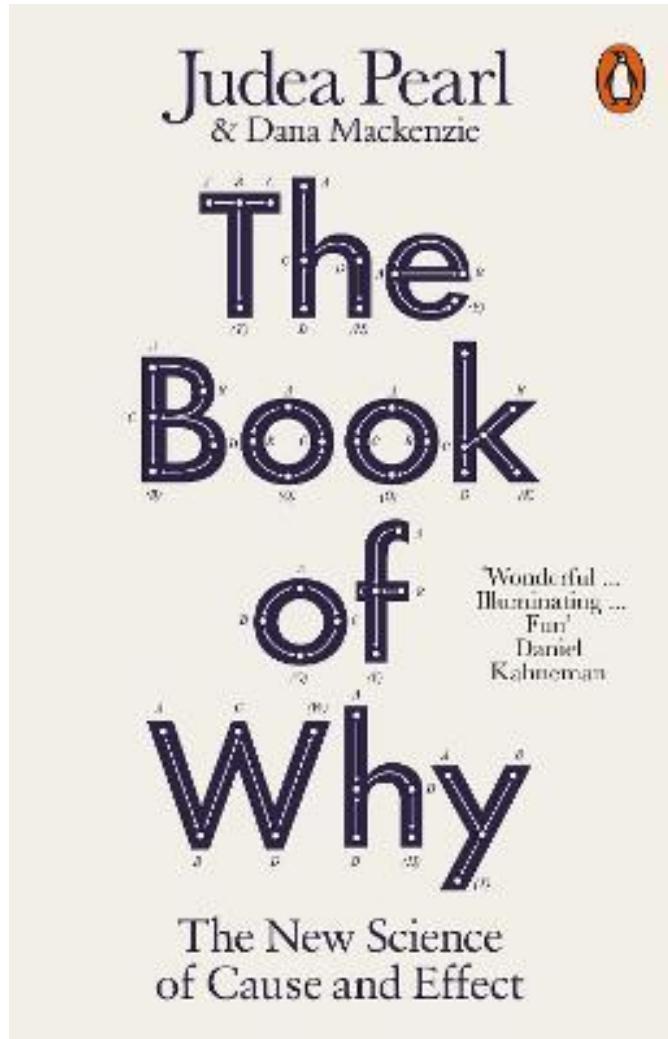
Mid 1960s study by Yerushalmy on 15,000 children found that low birthweight babies of smoking mothers had better survival than low birthweight babies of nonsmoking mothers.



Intuition-based explanation is that babies with low birthweight from non-smoking mothers are likely ones who have some serious birth defects that are more serious than having a smoking mother.

(Do Not) Control for X

More on causal inference



Frame the Experiment Fairly

Variation/Treatment/Intervention can impact how groups behave

#ทุบโต๊ะข่าว #AmarinTV34
เปิดใจ "ครูรุ่ม" สำนักผู้ดูแลเด็กอ้างเครียดแม่ป่วย
ห้ออยากรตาย ถามแคนี้เลวหรือ? | ทุบโต๊ะ^{ช่าว} | 26/09/63
123K views

778 likes, 177 dislikes, Share, Save, Report

AMARIN TVHD 11.1M subscribers, SUBSCRIBE

Comments • 1,753, ▾

In next Autoplay, Send, Comments have moved, GO TO COMMENTS

Control: comment at bottom
Test: comment on top

Multiple Experiments

The more you slice and dice, the more you need to be sure they are random

If you are running multiple experiments at the same time, you need to make sure than each other experiment is controlled for. For instance, if red variation got more low price, it might convert better but not because it was red but because the product was cheaper.

Packet color	Red	Grey		
Price	Low	Mid	High	
Title font	Bold	Italic	Underlined	Normal

Sunflower Seeds Packet A/B Test

Design journal



www.hamzada.com/sunflower-seeds?variation=A



www.hamzada.com/sunflower-seeds?variation=B

1. Metric - # payment / # cookie-days; each cookie is a Bernoulli trial (or the metric follows normalized binomial distribution)
2. 50/50 split on cookies; run separate tests by cookies coming from direct

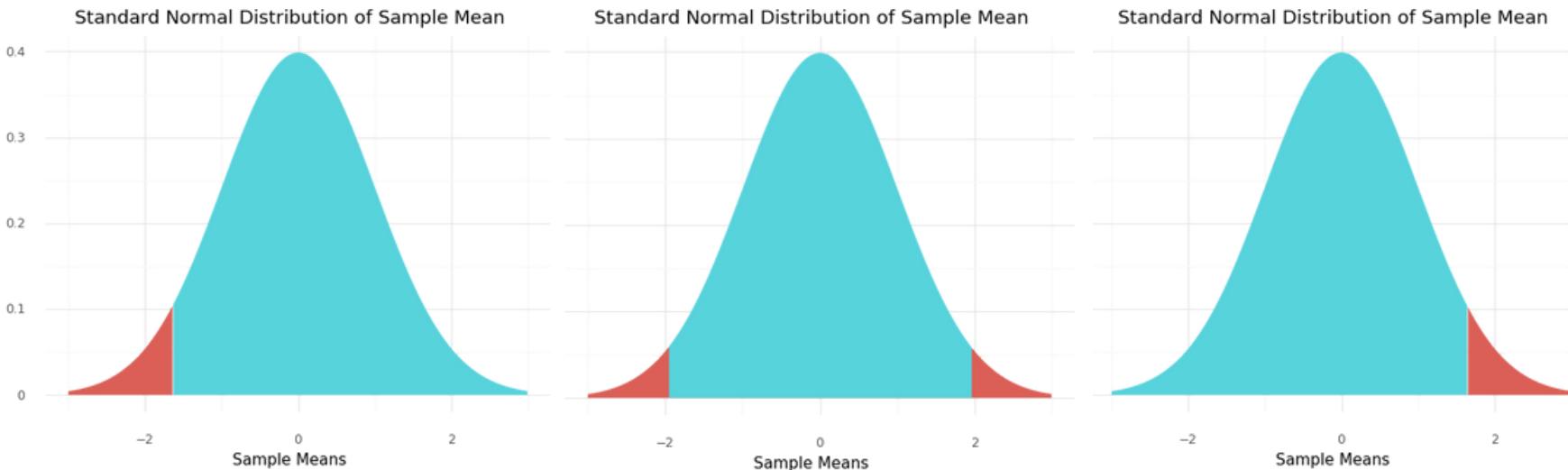
Choose statistical tests and validate their assumptions

See [frequentist.ipynb](#)

1. What frequentist hypothesis tests are saying
2. What frequentist hypothesis tests are NOT saying

What Frequentist Hypothesis Tests Are Saying

Assumed that **what we think is true** (H_0 : no difference in conversion),
the chance (p-value) of us seeing sample mean values that are more extreme than
what we are seeing right now (our Z score) is rarer than than the threshold of
false positive rate we can accept (**statistical significance**; 1%, 5%, 10%)



H_0 : difference is positive

H_0 : difference is zero

H_0 : difference is negative

*Note that more vs less comparisons have Z-score thresholds than are less extreme since they only take care of one tail of the distribution

What Frequentist Hypothesis Tests Are NOT Saying

Misuse of p-values

- The p-value is not the probability that the null hypothesis is true, or the probability that the alternative hypothesis is false.
- The p-value is not the probability that the observed effects were produced by random chance alone.
- The 0.05 significance level is merely a convention.
- The p-value does not indicate the size or importance of the observed effect.
- The p-value is not the observed false positive rate; that depends on the prevalence of the data.

Sunflower Seeds Packet A/B Test

Design journal



www.hamzada.com/sunflower-seeds?variation=A



www.hamzada.com/sunflower-seeds?variation=B

1. Metric - # payment / # cookie-days; each cookie is a Bernoulli trial (or the metric follows normalized binomial distribution)
2. 50/50 split on cookies; run separate tests by cookies coming from direct
3. Implement one-tailed Z test at 5% significance level

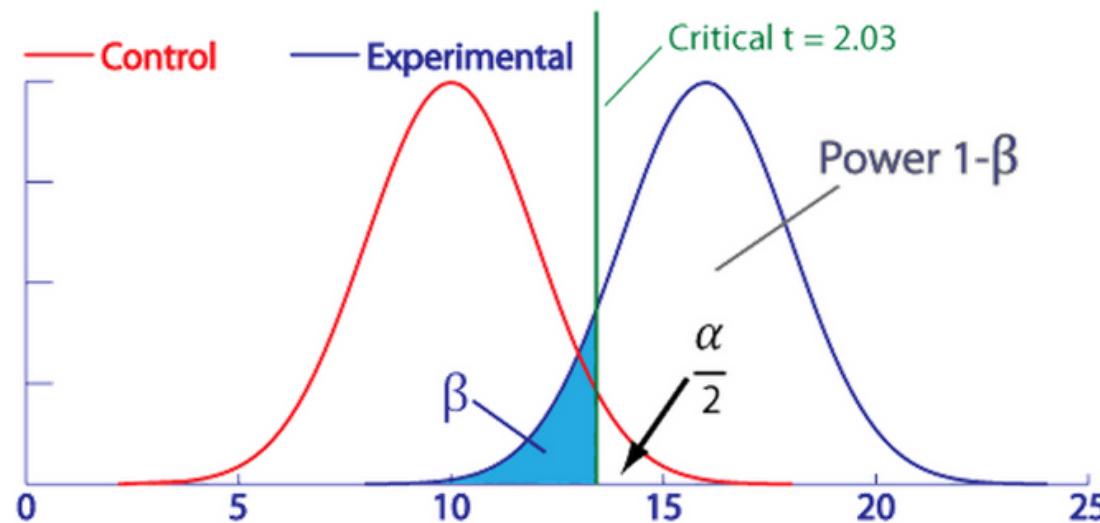
Decide on stopping criteria

Many frequentist test are significant if you run them long enough

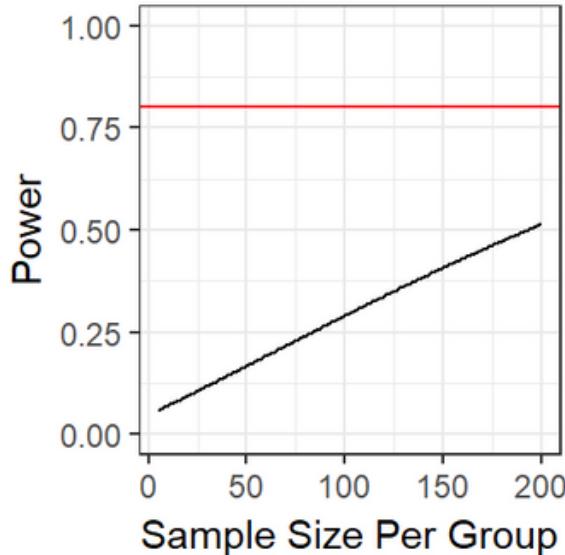
1. Minimum detectable effect
2. A/A tests
3. Trends and seasonality

Minimum Detectable Effect

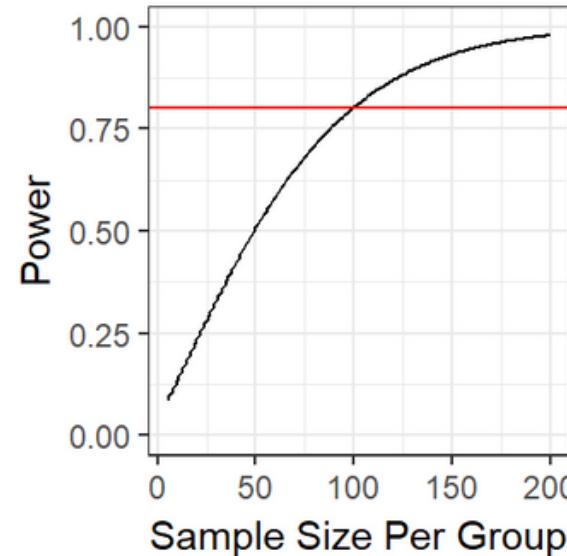
Effect size, power (true positive) and significance level (false positive)



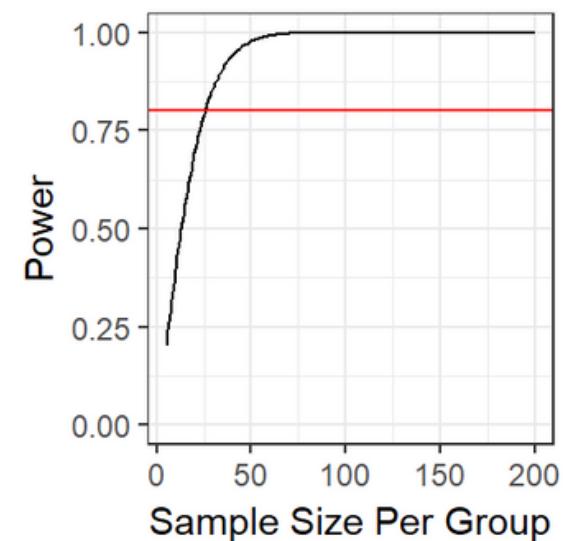
$d = .2, \alpha = .05, BS$



$d = .4, \alpha = .05, BS$

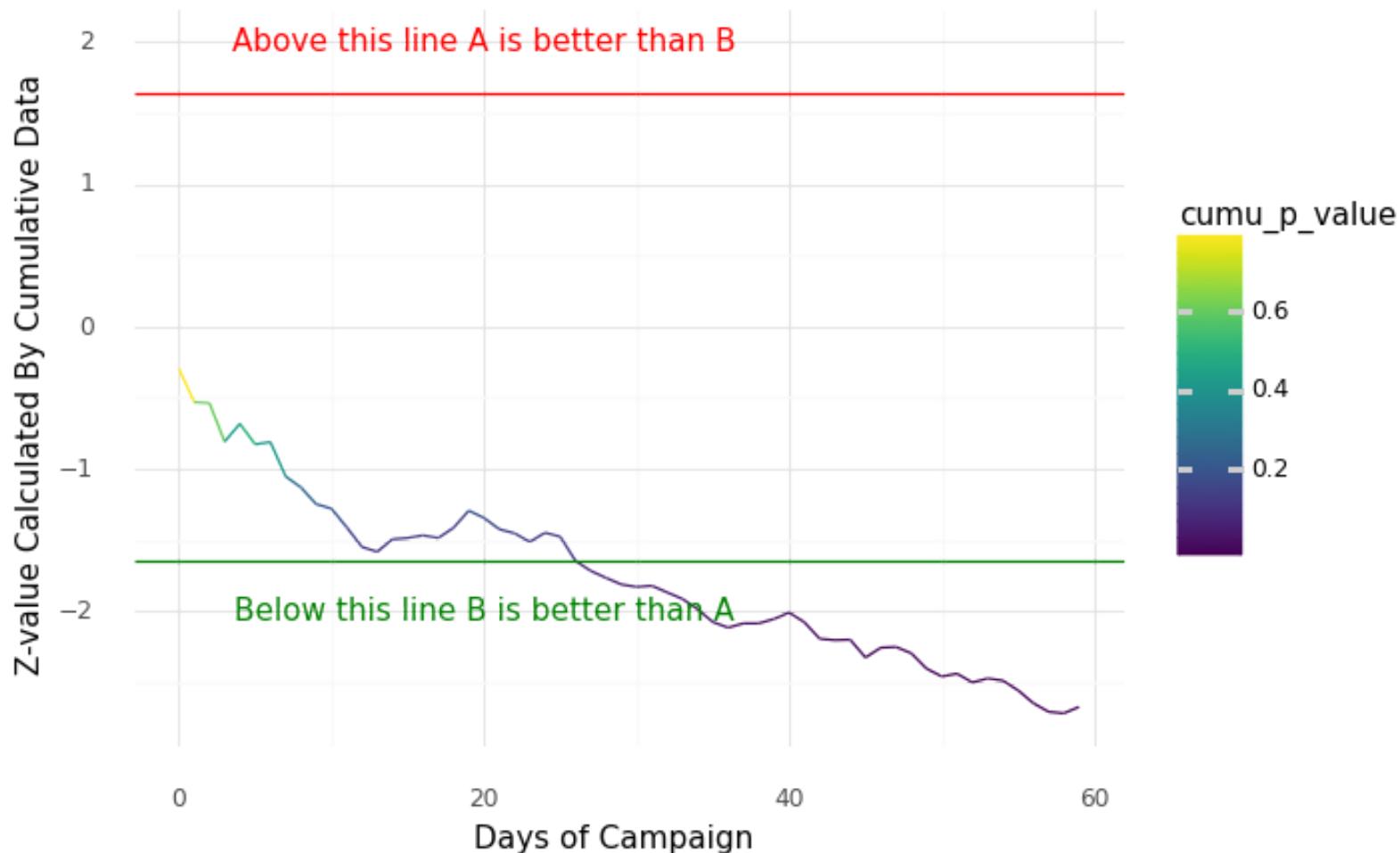


$d = .8, \alpha = .05, BS$



Minimum Detectable Effect

Many frequentist tests are statistically significant if you run them long enough



Minimum Detectable Effect

How we constructed our test statistics

observed
difference

usually 0

$$\bar{Z}_j = \frac{\bar{X}_j - \mu}{\sigma/\sqrt{n}}$$

**standard deviation
of our data**

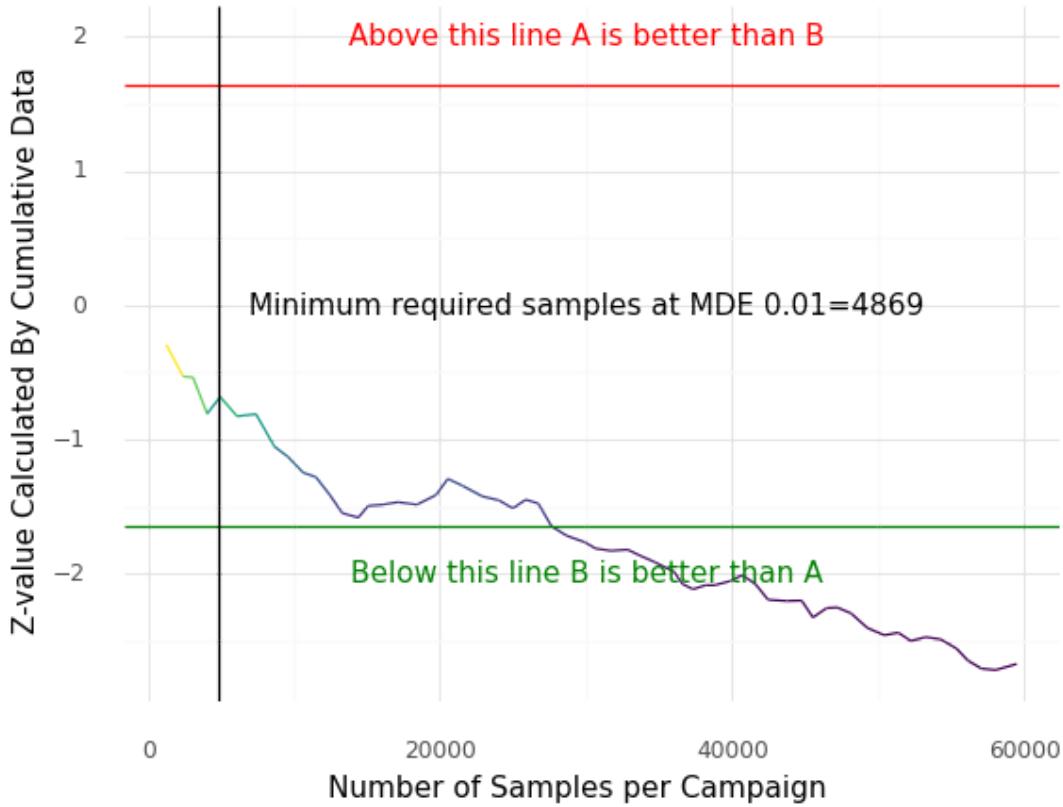
higher variation in data means
differences (or lack thereof)
will be more difficult to detect

number of samples

higher number of samples will
make the differences (or lack
thereof) easier to detect

Minimum Detectable Effect

Back calculate required sample size per variant



$$Z_\alpha = \frac{MDE - \mu}{\sqrt{\sigma^2 * (\frac{1}{n} + \frac{1}{mn})}}$$

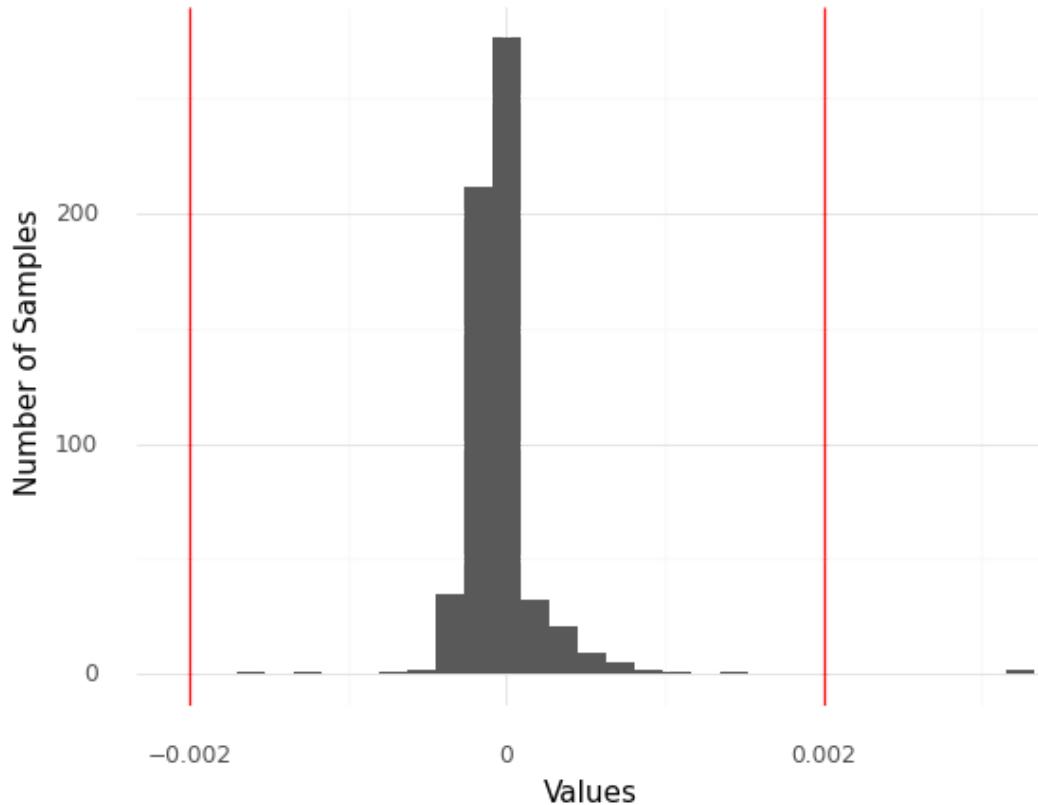
$$\frac{(m+1)\sigma^2}{mn} = \left(\frac{MDE}{Z_\alpha}\right)^2$$

$$n = \frac{m+1}{m} \left(\frac{Z_\alpha \sigma}{MDE}\right)^2$$

$$n = 2 \left(\frac{Z_\alpha \sigma}{MDE}\right)^2; m = 1$$

A/A Tests

A/A tests to see the distribution of differences between groups

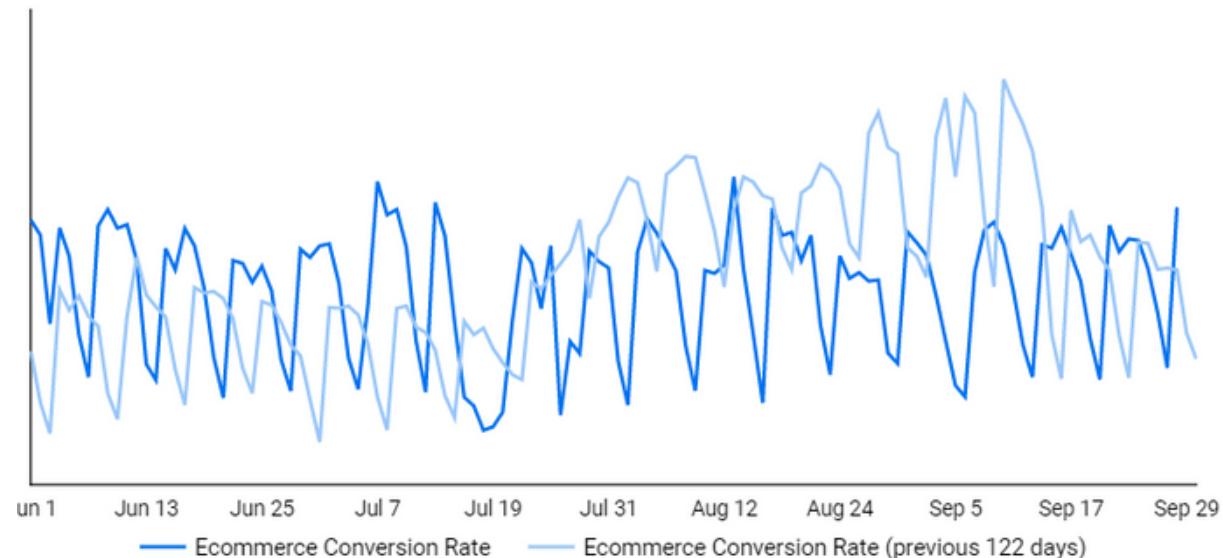


- Intentionally split cookies into control and control groups
- Show both of them the same variation
- Plot the distribution of differences between conversion rates
- A/A test results can also be used to estimate pooled sample variance empirically; Google's Udacity course discusses this extensively.

Trends and Seasonality

Run until required samples are met or over all known seasonality

- Run full length of the seasonality such as weekend shoppers
- Normalize by year-on-year data to de-trend



Sunflower Seeds Packet A/B Test

Design journal



www.hamzada.com/sunflower-seeds?variation=A



www.hamzada.com/sunflower-seeds?variation=B

1. Metric - # payment / # cookie-days; each cookie is a Bernoulli trial (or the metric follows normalized binomial distribution)
2. 50/50 split on cookies; run separate tests by cookies coming from direct
3. Implement one-tailed Z test at 5% significance level
4. Assume MDE of 1% based on A/A tests and run until 5,000 cookies on each variation and at least one week

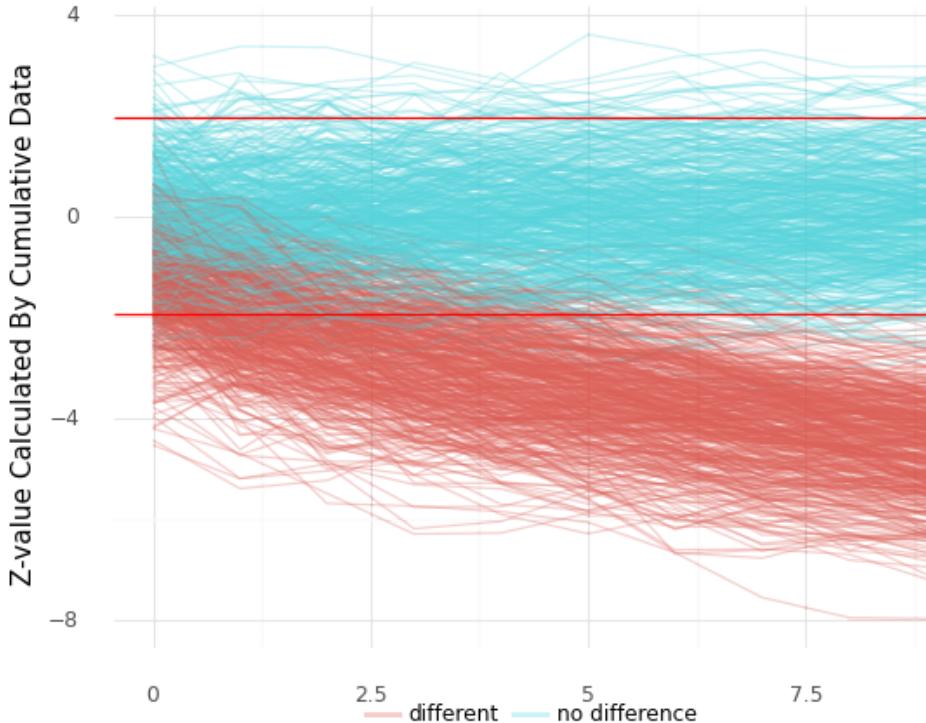
Run and monitor the experiment

Keep your tests in line

1. Do not peek
2. Sanity check
3. Post-test monitoring

Do Not Peek

Peeking results earlier than required samples will break your promise



Given the null hypothesis is true, frequentist tests promise to keep false positive rate lower than the significance threshold. Peeking earlier multiple times will break this promise.

Out of 1,000 simulations per group, 99.6% simulations with real difference reject H₀ by peeking (99.6% at the end)
22.4% simulations with no difference reject H₀ by peeking (**6.4%** at the end)



Sanity Check

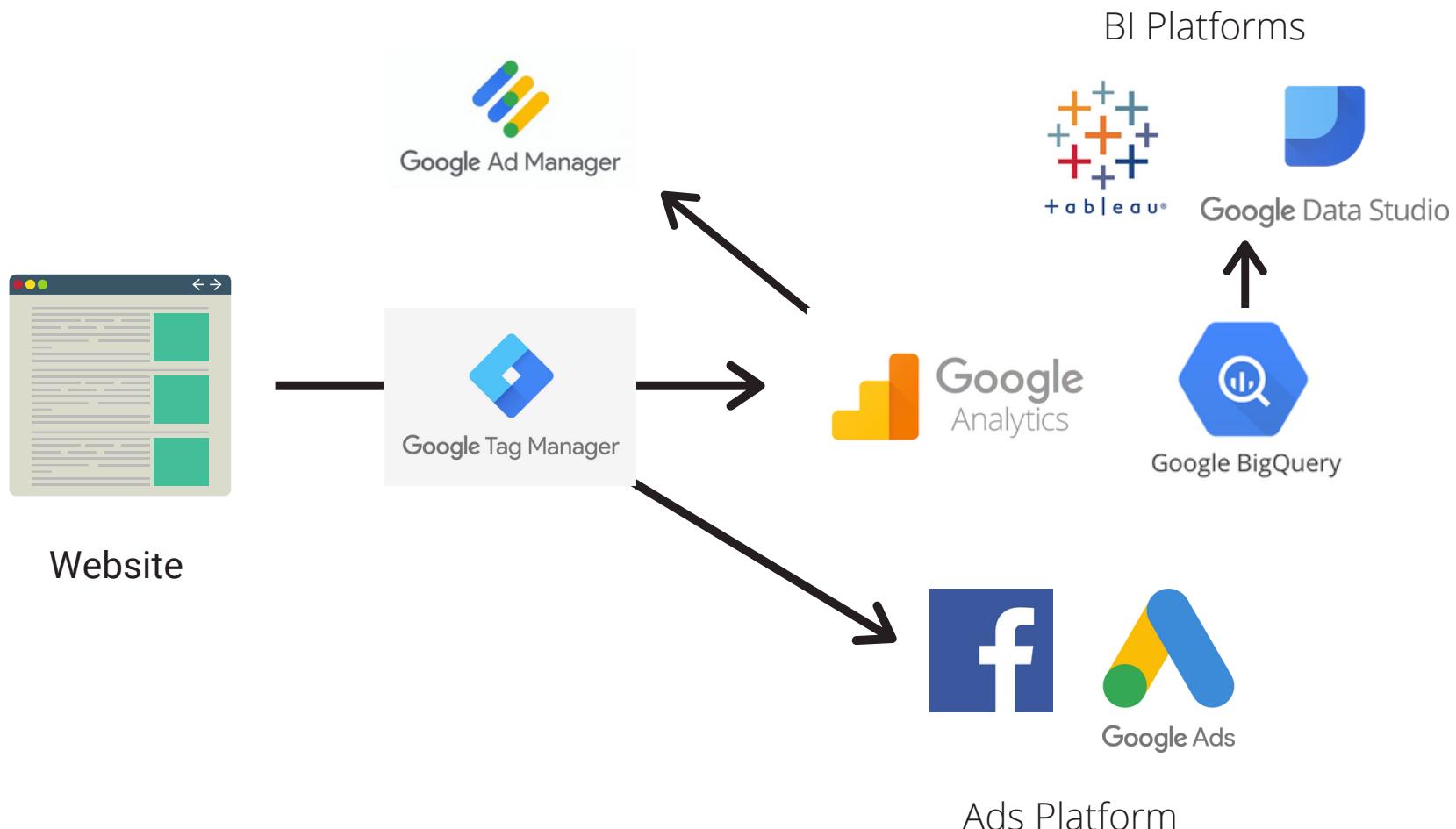
Is everything going as planned?

1. Check if your groups are split by what you intend; if we are testing by cookies and one cookie sees both variations, that would be a disaster
2. Check if your control variables are controlled
3. Twyman's law - any statistic that appears interesting is almost certainly a mistake; try to see if the splitting mechanism works as intended
 - a. Developers use random() to show variations instead of cookie-based splitting
 - b. One variation does not load
 - c. Tracking does not work

Sanity Check

Web tracking architecture

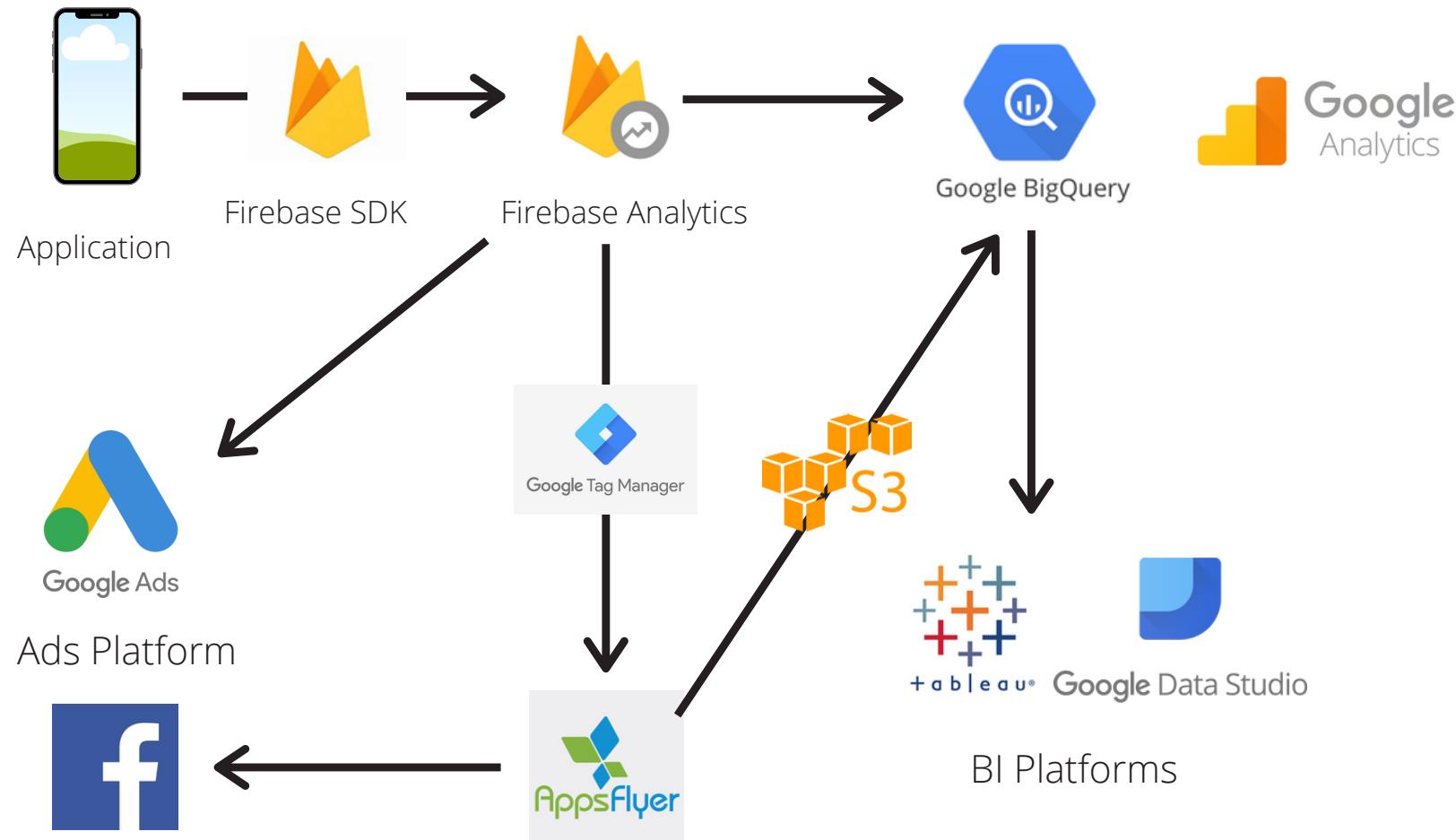
Google Tag Manager is a powerful tool that can aggregate web tracking scripts from different providers and send to analytic dashboards and ad platforms.



Sanity Check

App tracking architecture

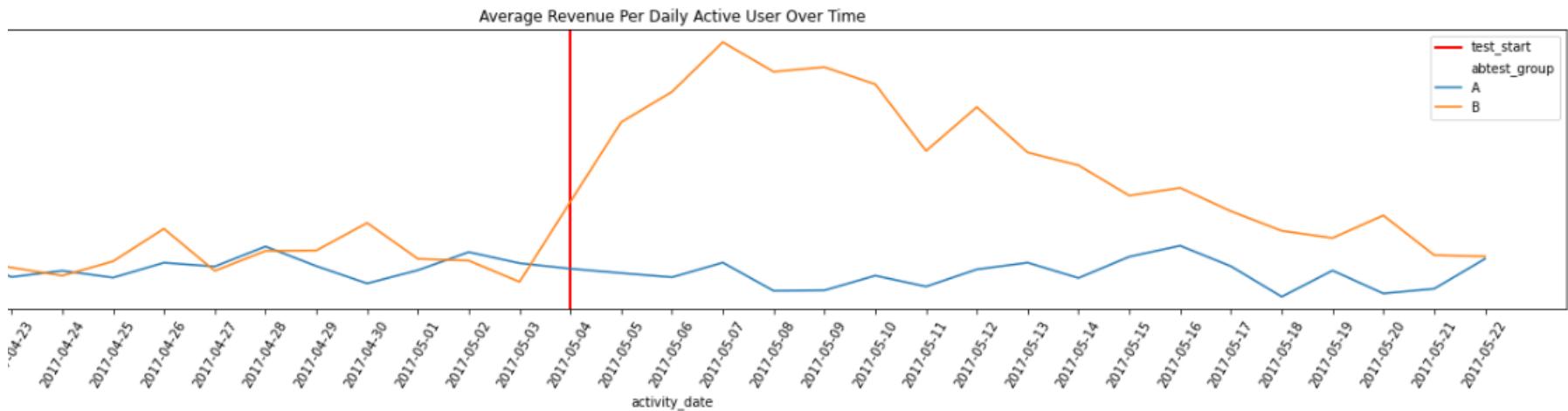
Most app tracking happens through Firebase SDK through which we can forward the data to GTM, analytic dashboards and ads platforms.



Post-test Monitoring

Monitor if the changes persist or just a one-hit wonder

- Customers might be interested because of the novelty but converges to control group over time
- Leave small portion of control group to verify



Sunflower Seeds Packet A/B Test

Design journal



www.hamzada.com/sunflower-seeds?variation=A



www.hamzada.com/sunflower-seeds?variation=B

1. Metric - # payment / # cookie-days; each cookie is a Bernoulli trial (or the metric follows normalized binomial distribution)
2. 50/50 split on cookies; run separate tests by cookies coming from direct
3. Implement one-tailed Z test at 5% significance level
4. Assume MDE of 1% based on A/A tests and run until X samples on each variation and at least one week
5. Check if cookies are viewing only assigned variations; leave 10% on control afterwards

Analyze results and suggest actions

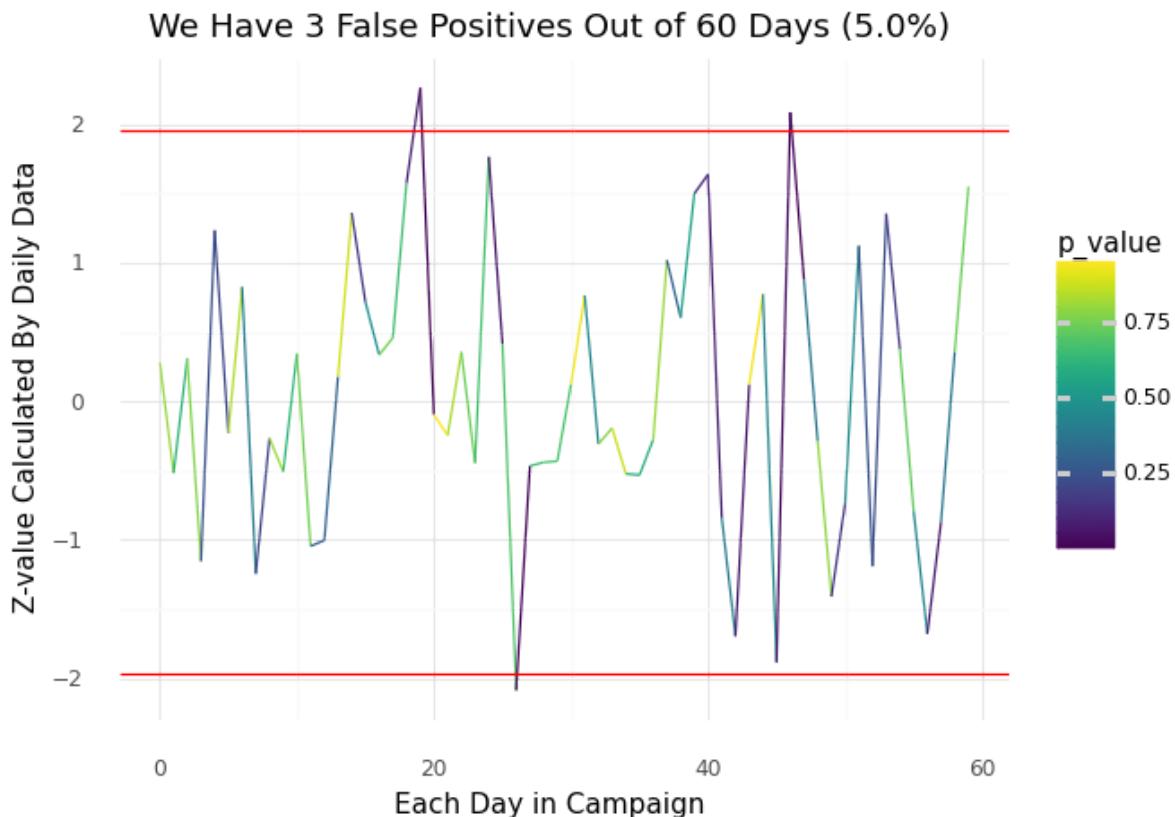
We are running a business after all

1. Multiple test corrections
2. Take actions; understand the risks

Multiple Test Corrections

If you run the tests enough times, you will get statistical significance

If you run 60 tests best on daily data, 3 of them will reject H₀, even if it is both groups have the same true conversion rates



Multiple Test Corrections

Bonferroni and Sidak

- **Bonferroni corrections** - divide alpha by number of tests; very conservative
- **Sidak corrections** - assume the tests are independent, the chances that all tests are not statistically significant given null hypothesis is true (aka multiple-test false positive rate) is

$$\text{alpha_overall} = 1 - (1 - \text{alpha_sidak})^{\text{(number of tests)}}$$

$$\text{alpha_sidak} = 1 - (1 - \text{alpha_overall})^{(1/\text{number of tests})}$$

Example: $\text{alpha_overall} = 0.05$; 10 tests

- Bonferroni corrections - $0.05/10 = 0.005$
- Sidak corrections - $1 - (1 - 0.05)^{10} = 0.005116$

Note that there are also more complicated and less conservative corrections such as the Benjamini-Hochberg method

Take Actions; Understand the Risks

At the end of the day, we are running a business

A Dirty Dozen: Twelve P-Value Misconceptions

Table 1 Twelve P-Value Misconceptions

1	If $P = .05$, the null hypothesis has only a 5% chance of being true.
2	A nonsignificant difference (eg, $P \geq .05$) means there is no difference between groups.
3	A statistically significant finding is clinically important.
4	Studies with P values on opposite sides of .05 are conflicting.
5	Studies with the same P value provide the same evidence against the null hypothesis.
6	$P = .05$ means that we have observed data that would occur only 5% of the time under the null hypothesis.
7	$P = .05$ and $P \leq .05$ mean the same thing.
8	P values are properly written as inequalities (eg, " $P \leq .02$ " when $P = .015$)
9	$P = .05$ means that if you reject the null hypothesis, the probability of a type I error is only 5%.
10	With a $P = .05$ threshold for significance, the chance of a type I error will be 5%.
11	You should use a one-sided P value when you don't care about a result in one direction, or a difference in that direction is impossible.
12	A scientific conclusion or treatment policy should be based on whether or not the P value is significant.

- Rejecting the null hypothesis does not mean that the alternative hypothesis is better *technically*, but we still make business decisions on it
- We tailor minimum detectable effect so that the winner is worth the investment; change button color vs new machine learning models

Sunflower Seeds Packet A/B Test

Design journal



www.hamzada.com/sunflower-seeds?variation=A



www.hamzada.com/sunflower-seeds?variation=B

1. Metric - # payment / # cookie-days; each cookie is a Bernoulli trial (or the metric follows normalized binomial distribution)
2. 50/50 split on cookies; run separate tests by cookies coming from direct
3. Implement one-tailed Z test at 5% significance level
4. Assume MDE of 1% based on A/A tests and run until X samples on each variation and at least one week
5. Check if cookies are viewing only assigned variations; leave 10% on control afterwards
6. Run one test at the end; use packets that win

Limitations

When to NOT do an A/B test

1. **Things that cannot be summarized into one or a few metrics**; are our users happy?
2. **Totally new things**; not apple-to-apple comparison; do a survey, focus group, design thinking
3. **Delayed results**; for example, does a change makes customer repurchase more? what if repurchase period is 3 months?
4. **One-off events**; no two big sales events such as 11.11 or Black Friday are the same
5. **If you cannot split groups independently**; offline store layout of the same store

A/B Testing in the Wild

1. Understand your business; you do A/B tests so that you can make real-world decisions, not because you are a calculator
2. Tracking, tracking, tracking
3. Going through the process once is more important than trying to make every step perfect
4. Explicitly state your assumptions and be prepared for the risks
5. Control groups will win a lot; it's how you respond to it

Useful Resources on A/B Testing

- Calculators
 - [Evan's Awesome A/B Test Tools](#)
 - [A/B Test Calculators by abtestguide.com](#)
 - [abtestoo - A/B Tests and MABs made easy.](#)
- Courses and readings
 - [Causal Inference Mixtape](#)
 - [ExP Experimentation Platform](#)
 - [Udacity's A/B Testing by Google](#)
 - [p-value and the base rate fallacy](#)
- Frameworks
 - [wasabi by Intuit](#)
 - [planout by Facebook](#)
 - [Google Optimize by Google](#)