[320] Web 5: A/B Testing

Tyler Caraza-Harter

Source for Examples/Lessons

Ronny Kohavi Keynote Talk at KDD conference (Knowledge Discovery and Data Mining)

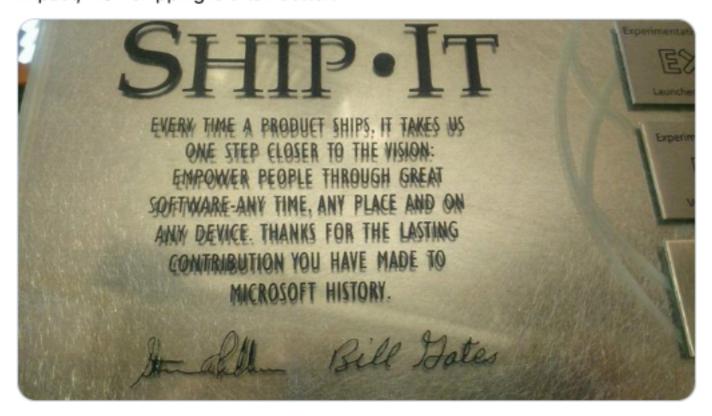
Title: Online Controlled Experiments: Lessons from Running A/B/n Tests for 12 years

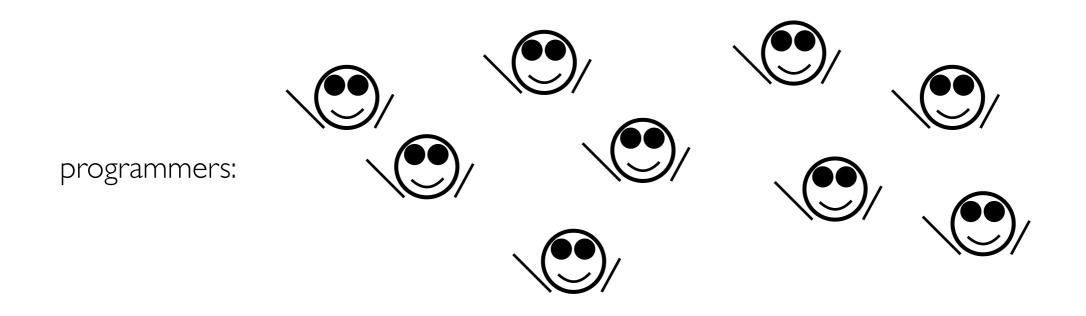
Video: https://exp-platform.com/kdd2015keynotekohavi/



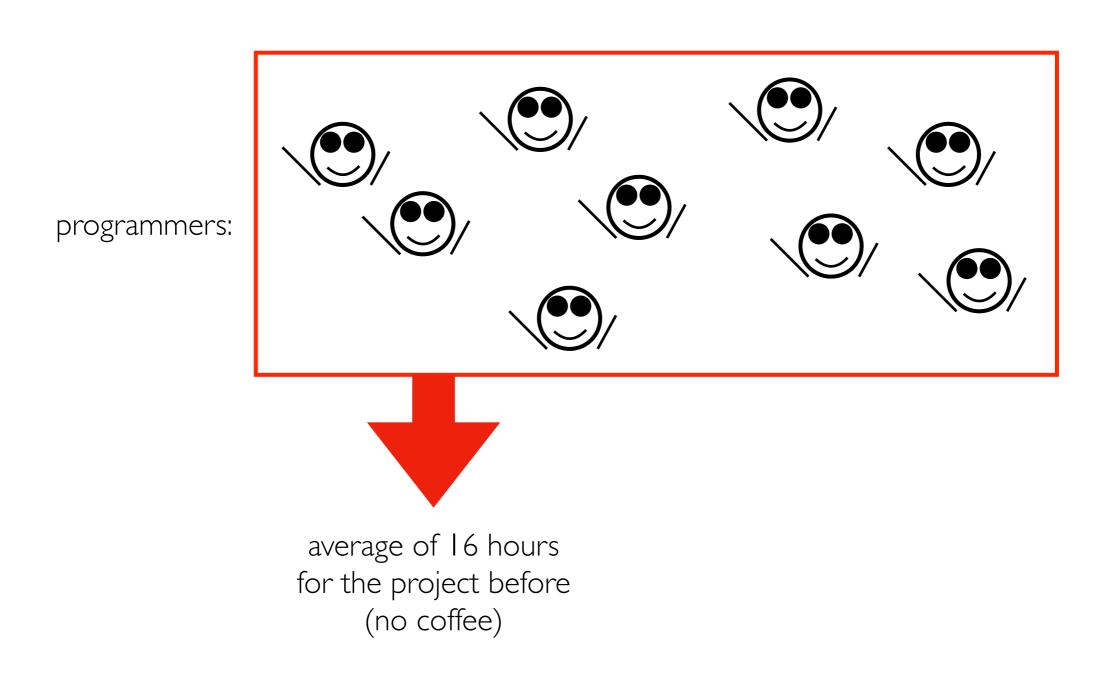
Ronny Kohavi @ronnyk · Nov 7, 2014

Microsoft stopped ship-it-awards today! With #abtesting, it's about userimpact; NOT shipping is often better!

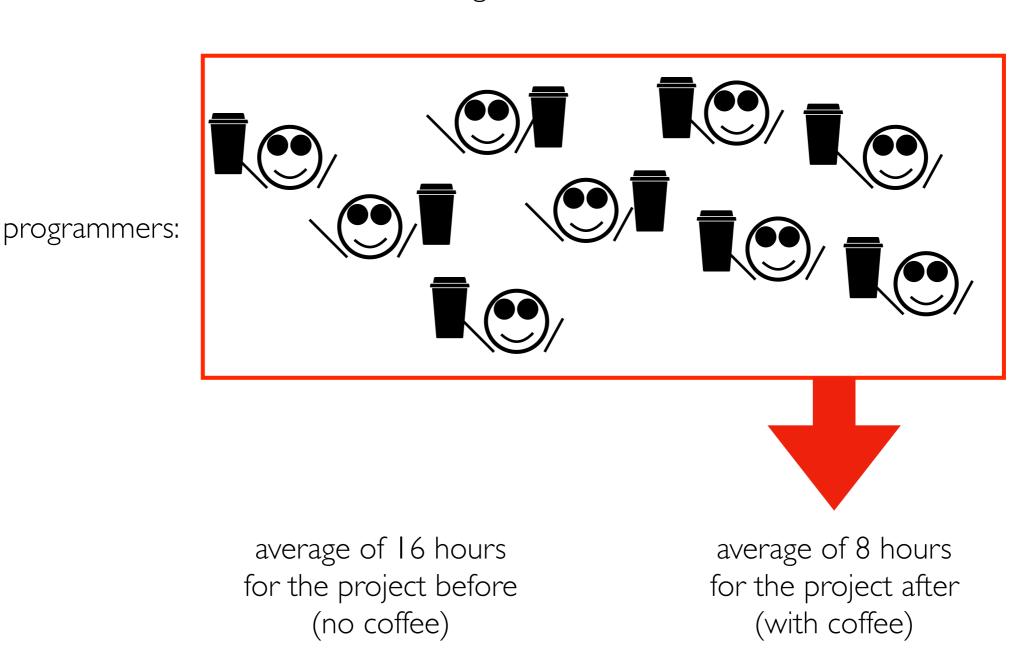




Design 1: before and after



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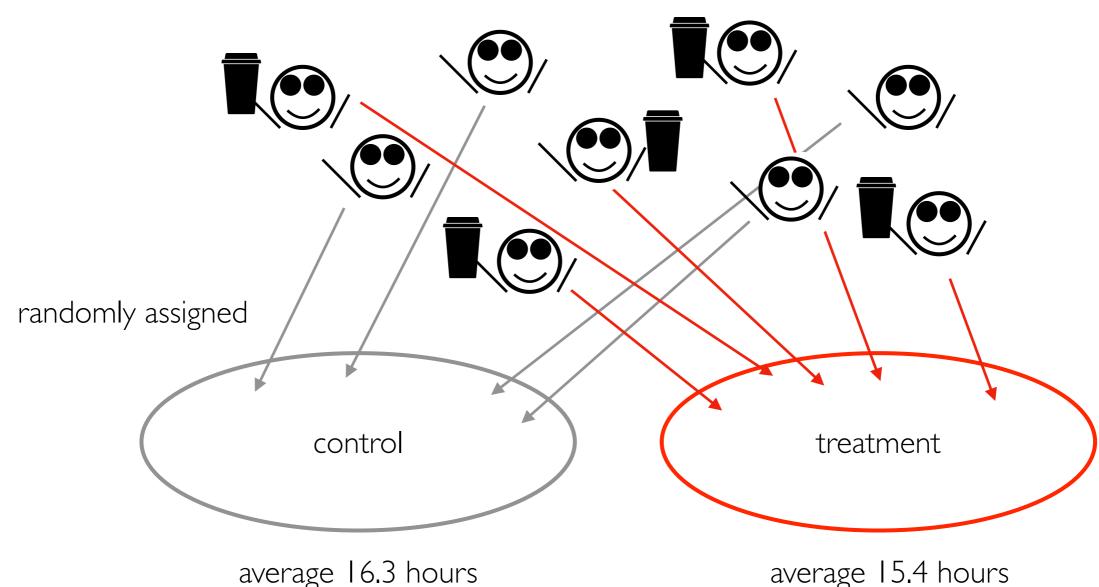
programmers:

concerns???

average of 16 hours for the project before (no coffee)

average of 8 hours for the project after (with coffee)

Design 2: randomly assigned control and treatment groups

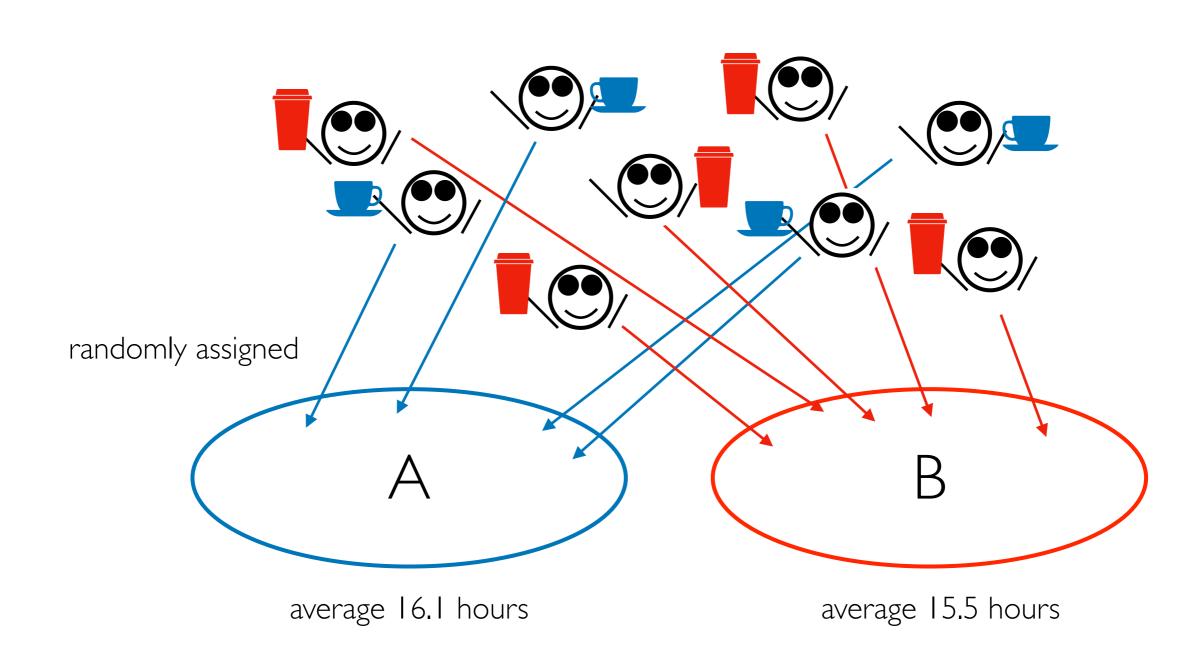


average 15.4 hours

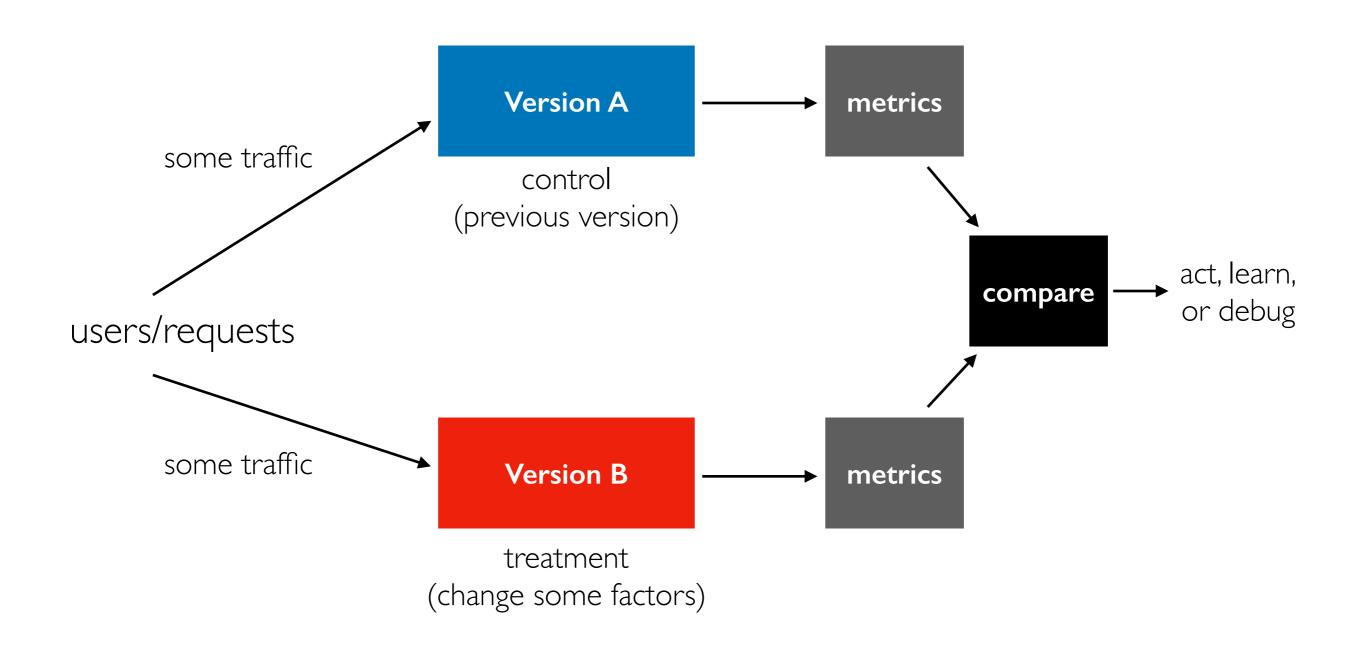
Experiment Design:

Is coffee or tea better for programming?

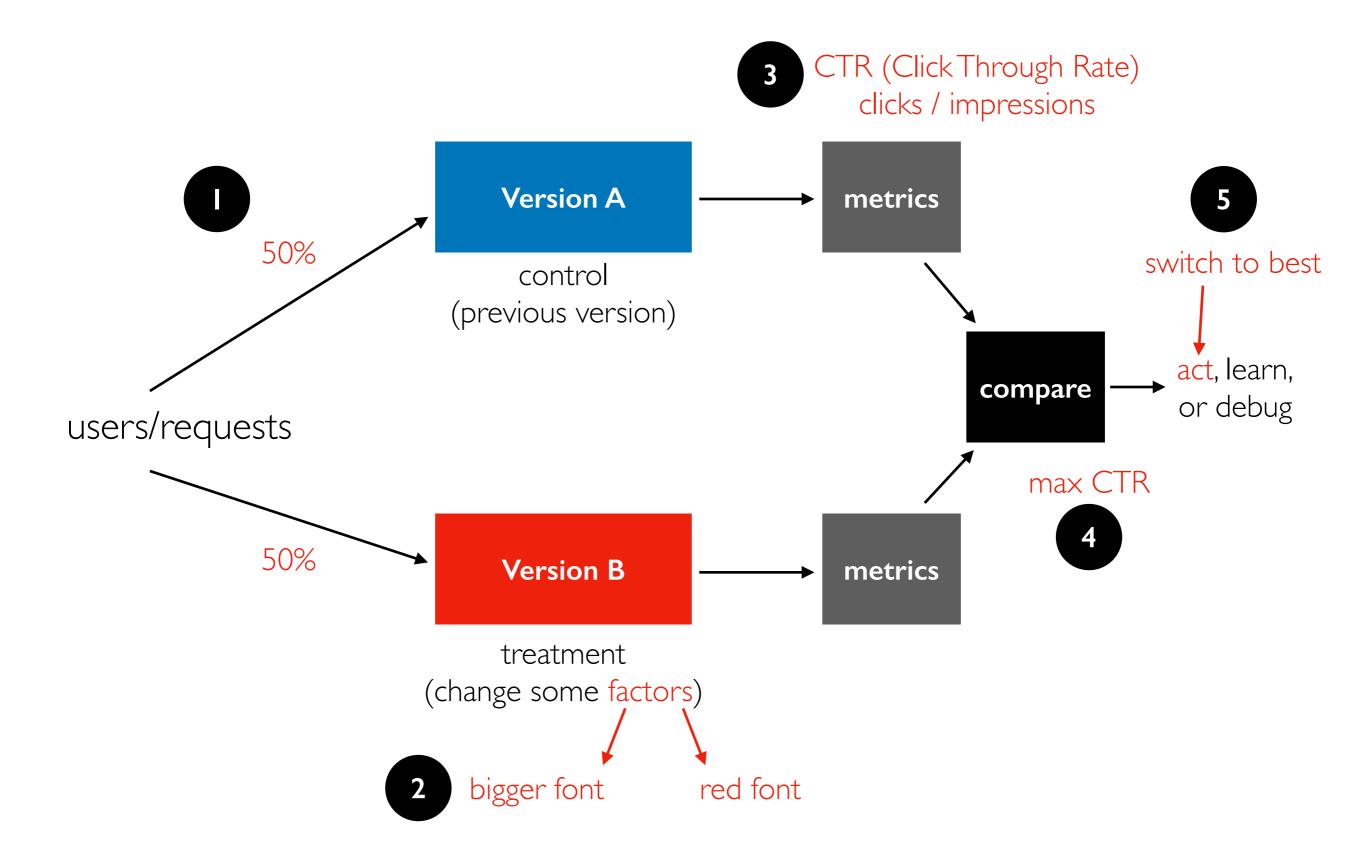
A/B Testing



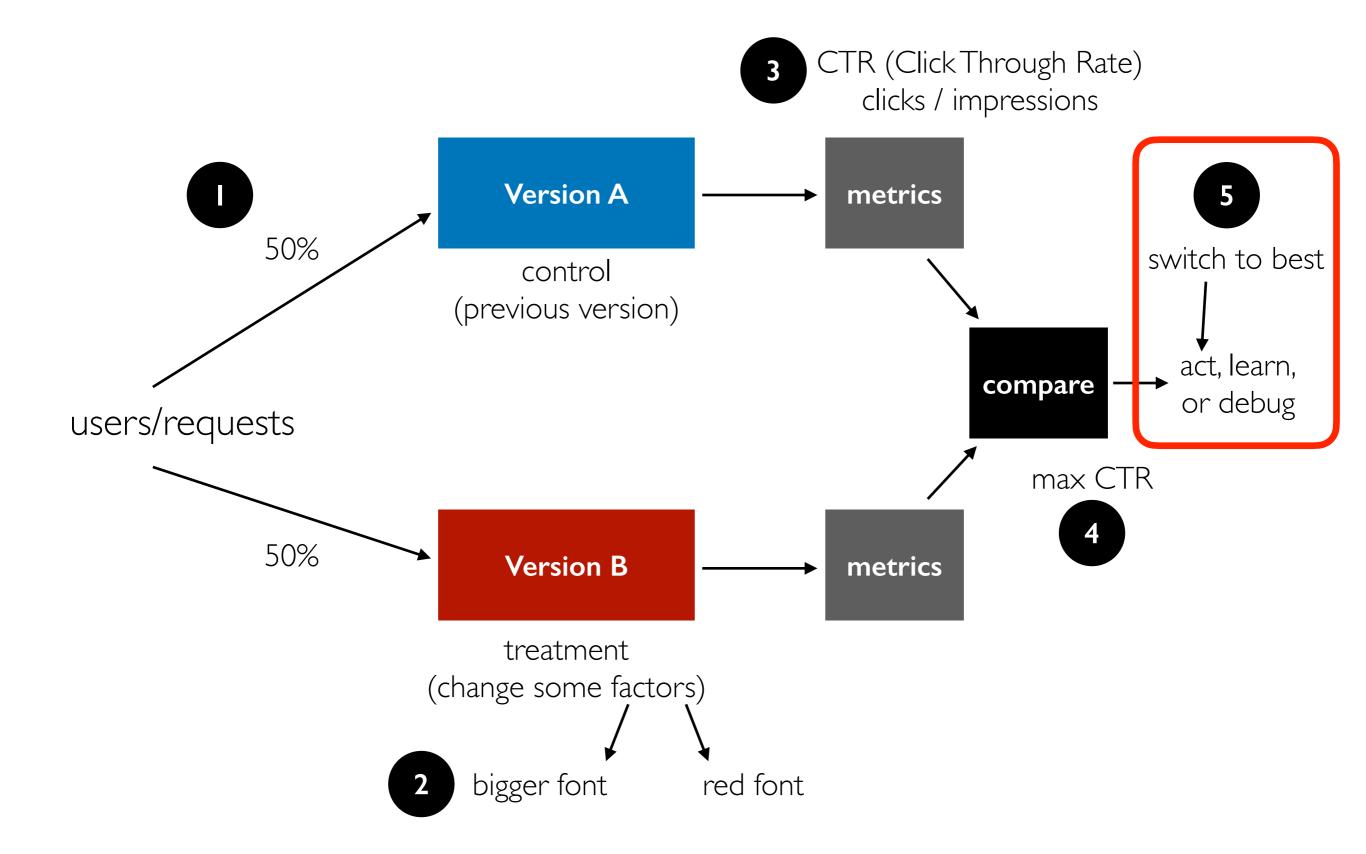
A/B Test Overview (for web applications!)



Example 1: Link to Donation Page

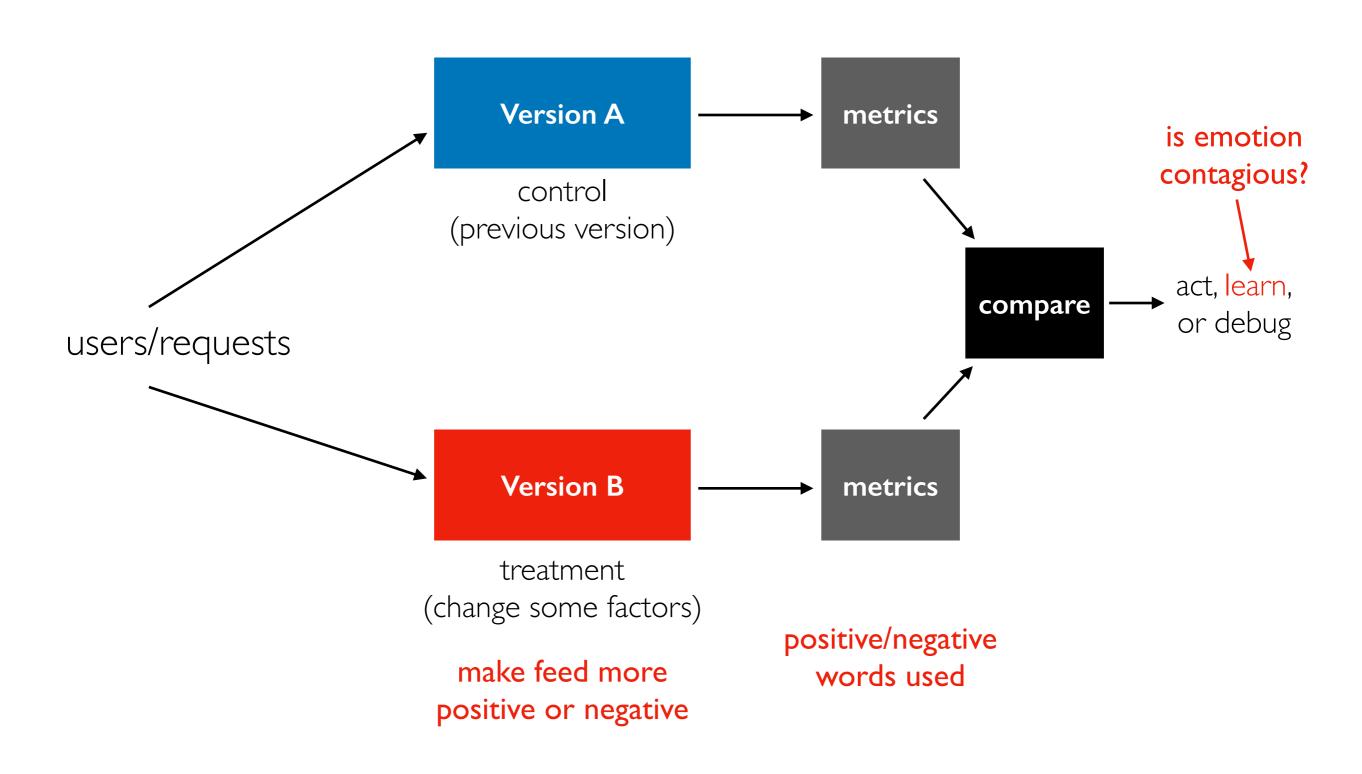


Lecture Outline



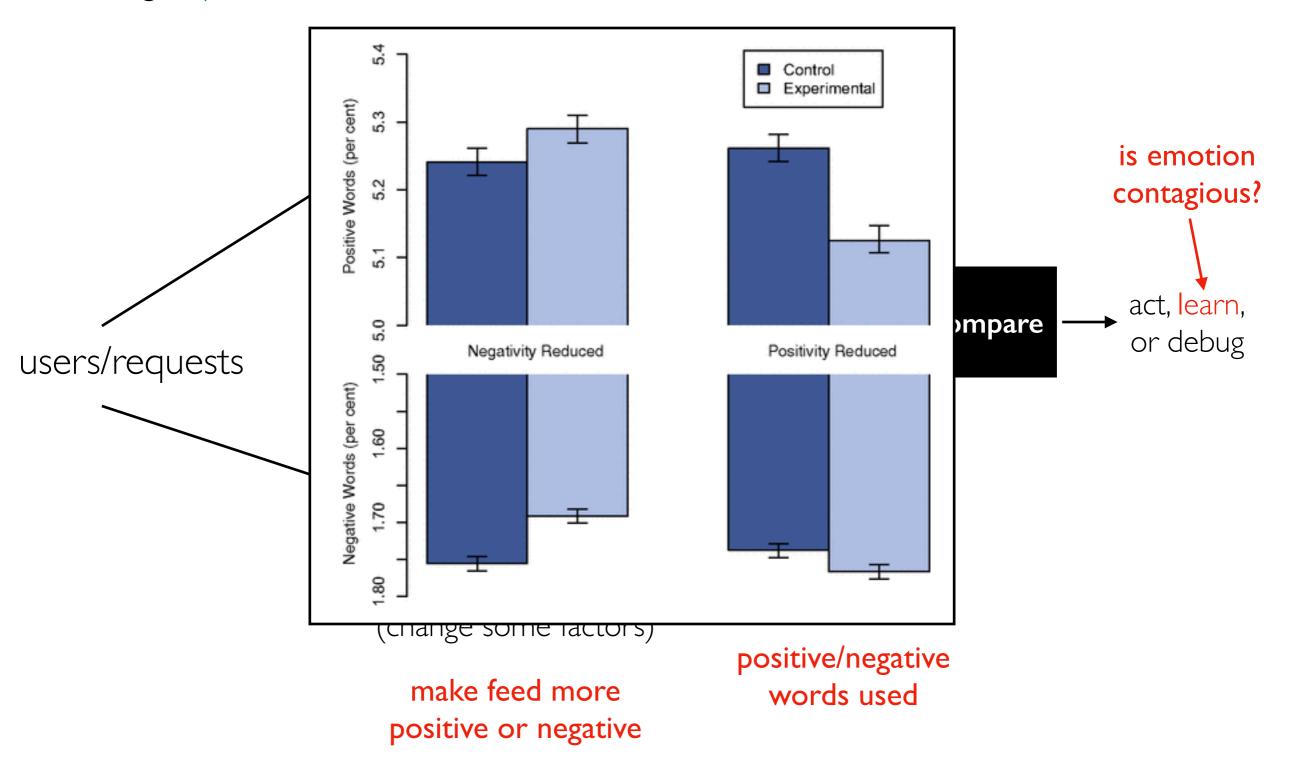
Example 2: Facebook Emotional Contagion Study

Reading: https://techcrunch.com/2014/06/29/ethics-in-a-data-driven-world/



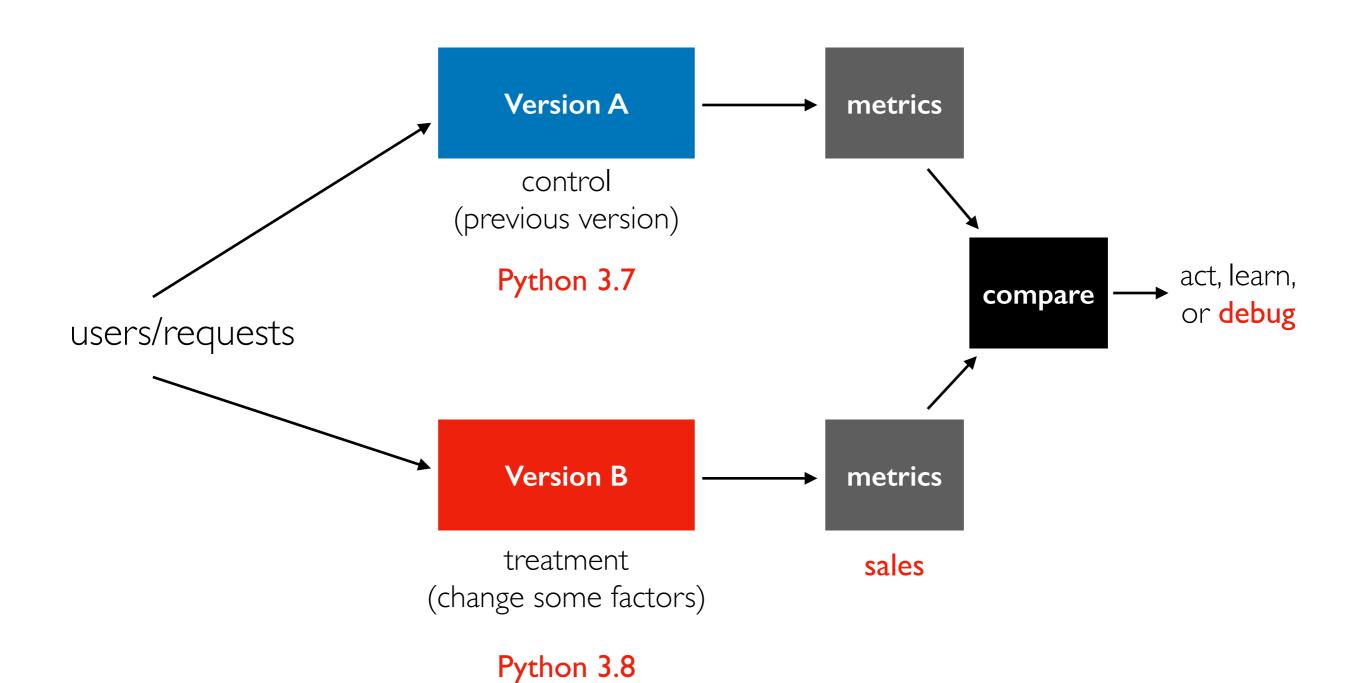
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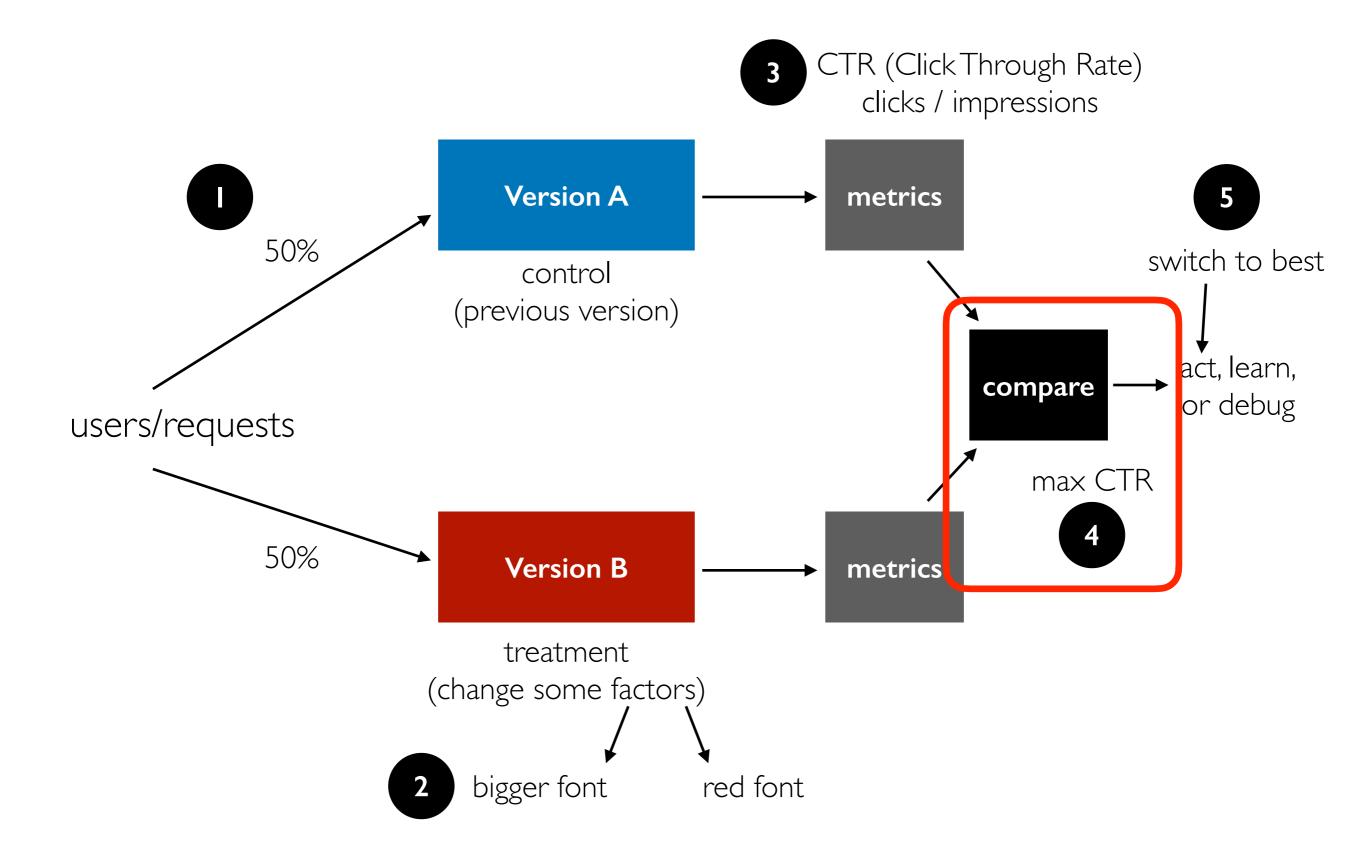


didn't need to submit to the IRB (Institutional Review Board) -- when should it be required?

Example 3: Update Python Version



Lecture Outline



Example Metric: CTR (Click-Through Rate)

CTR = clicks / impressions

"Impression" means user saw it

	click	no-click
A	12	68
В	6	14

df: contingency table

how many B impressions were there? what was B's CTR?

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	click	no-click
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how many B impressions were there? 20 what was B's CTR? 6/20 = 30%

Example Metric: CTR (Click-Through Rate)

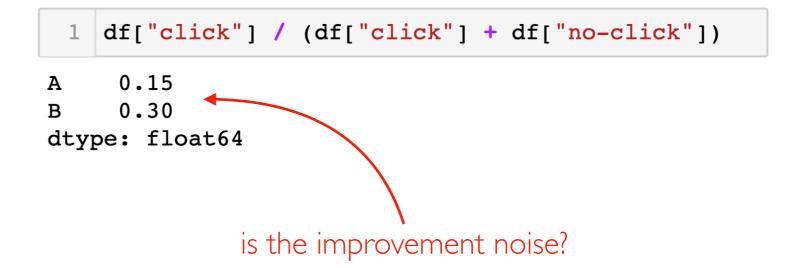
CTR = clicks / impressions

"Impression" means user saw it

click no-click

A 12 68B 6 14

df: contingency table



Example Metric: CTR (Click-Through Rate)

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click no-click

A	12	68
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```
1 df["click"] / (df["click"] + df["no-click"])
A      0.15
B      0.30
dtype: float64
```

df: contingency table

pip3 install scipy

```
import scipy.stats as stats
    _, pvalue = stats.fisher_exact(df)
pvalue
    _https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.fisher_exact.html
```

Example Metric: CTR (Click-Through Rate)

CTR = clicks / impressions

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p-value is probability of seeing a difference this extreme (or more) if both ratios were generated by the same underlying process (the one most likely to generate this)

Click		no-click
A	12	68
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"significant" means p-value is less than some threshold (e.g., 5%)

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false positive means it is significant even though underlying process is same

out of 200 neutral changes, how many will falsely show up as significant if we set our p-value threshold to 5%?

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click no-click

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```
1 import scipy.stats as stats
```

2 _, pvalue = stats.fisher_exact(df)

3 pvalue

https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.fisher_exact.html

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occasionally run A/A tests to make sure the system is working (false positive rate should be as expected)

df: contingency table

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3 outcomes, based on CTRs and significance

- A is significantly better
- B is significantly better
- neither wins



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3 outcomes, based on CTRs and significance

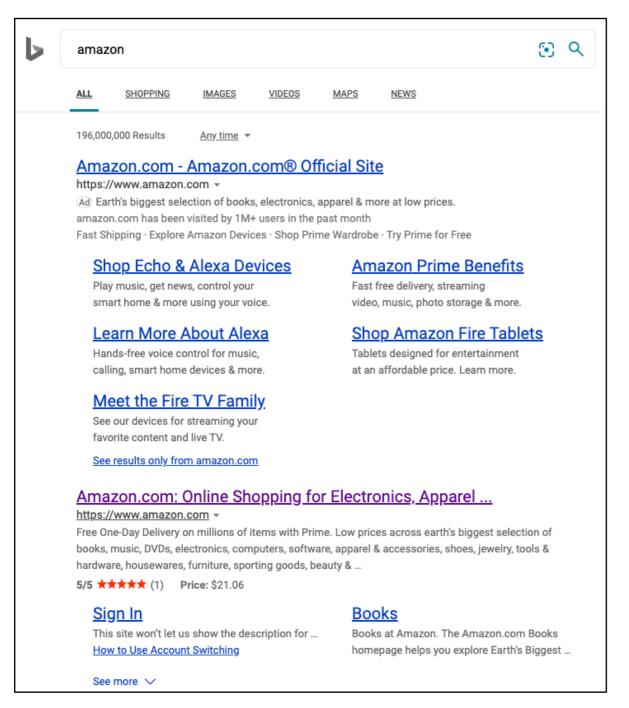
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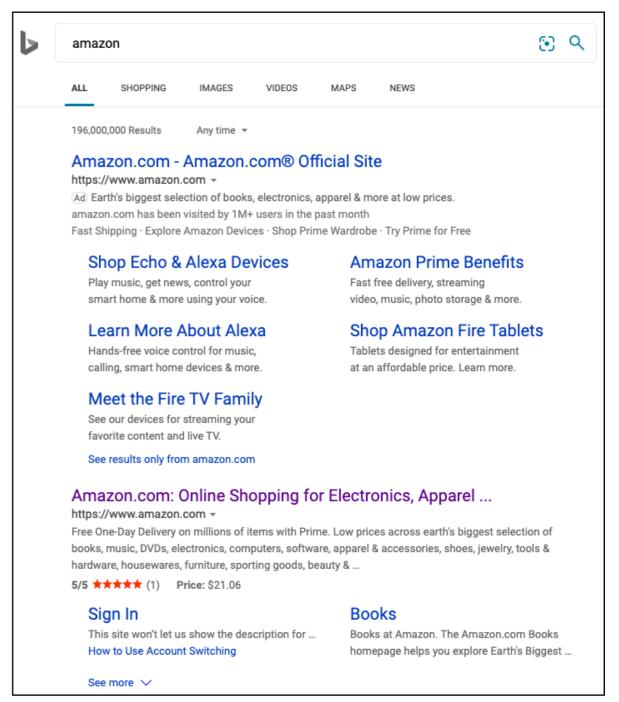
- collect more data
- ignore significance, just look at CTR (indecision may be the worst decision)
- choose previous version A (probably fewer bugs)
- choose new version B (for simplicity or other merits)

Which Version Has Higher Whole-page CTR?

Version A

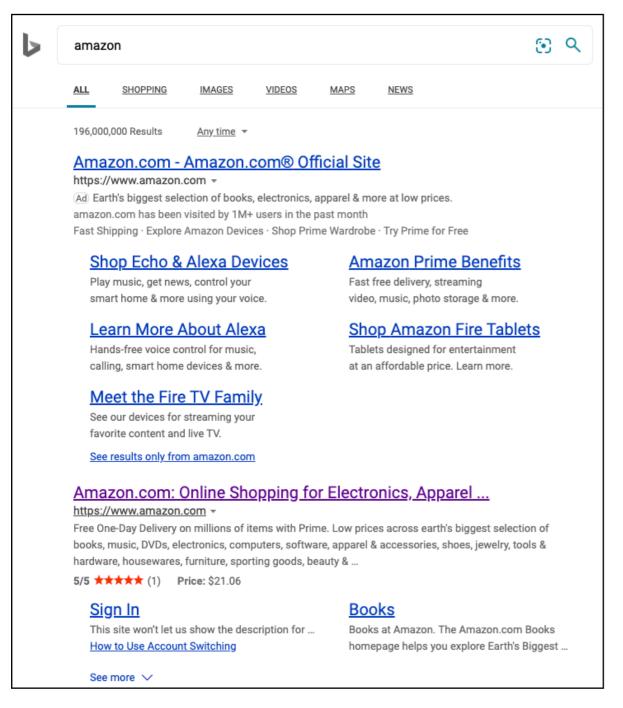


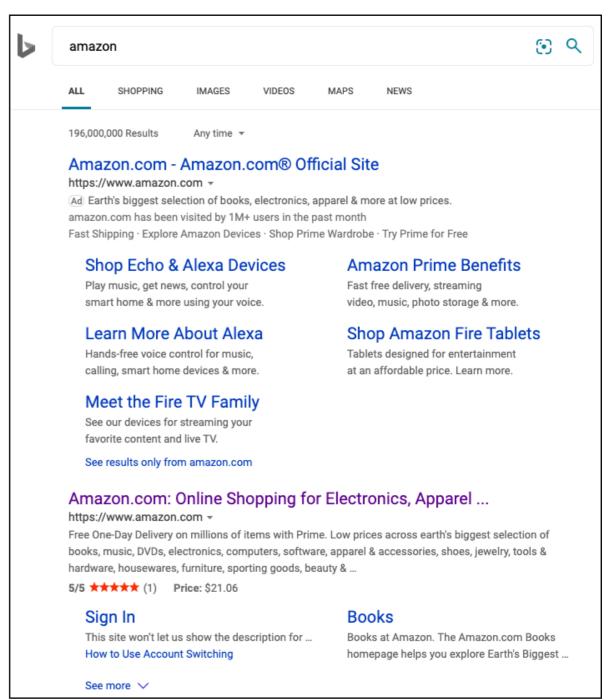
Version B



Which Version Has Higher Whole-page CTR?

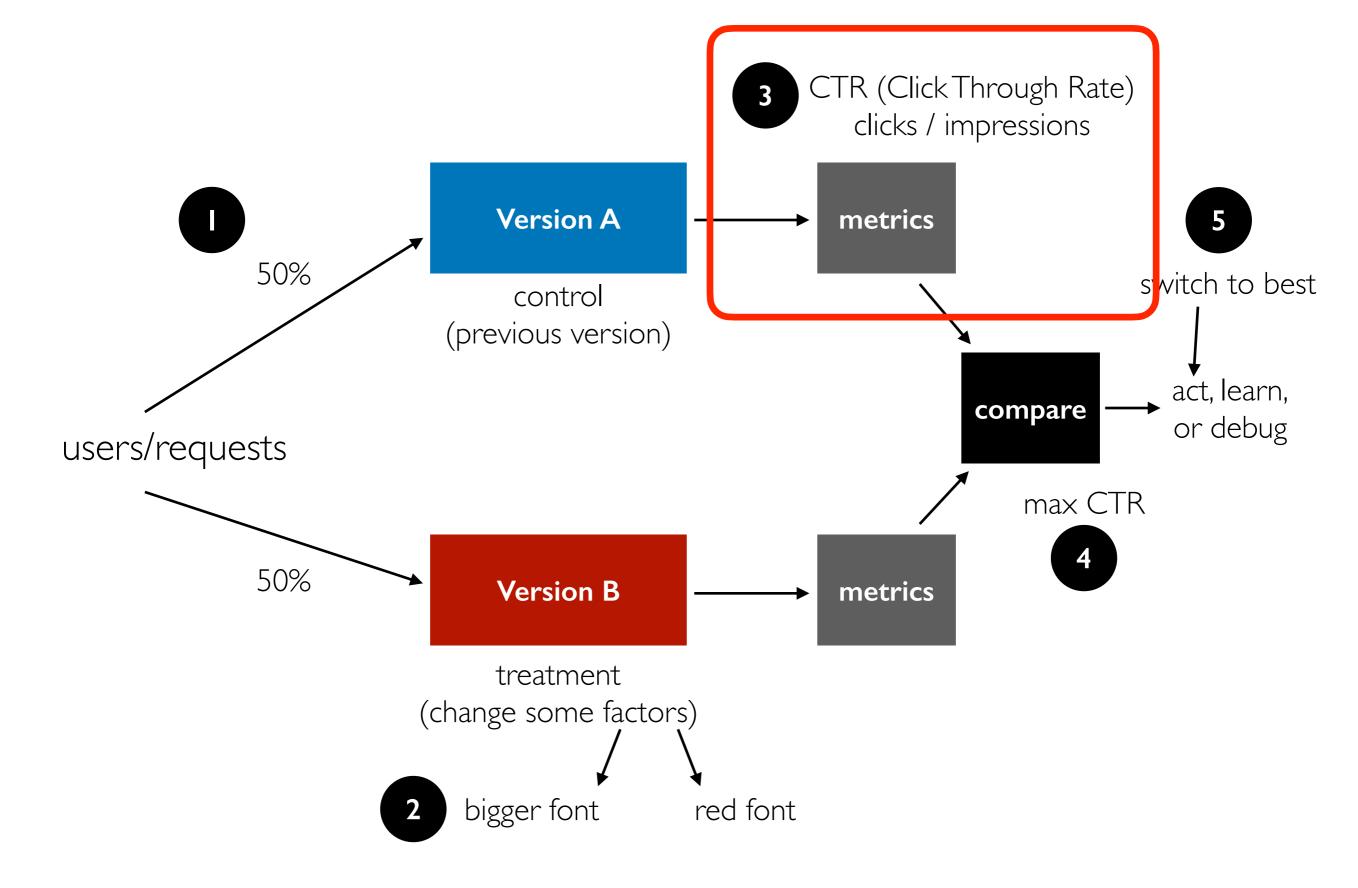
Version A Version B





Lesson: metrics should inform humans, not directly determine decisions

Lecture Outline



Things to measure:

- clicks -- when are they bad?

Things to measure:

- clicks
- scroll (did they read it?)
- subscribe/unsubscribe
- other ideas?

Things to measure:

- clicks
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- subscribe/unsubscribe
- purchases/returns
- hover (did they think about it?)
- shares
- likes/upvotes
- comments

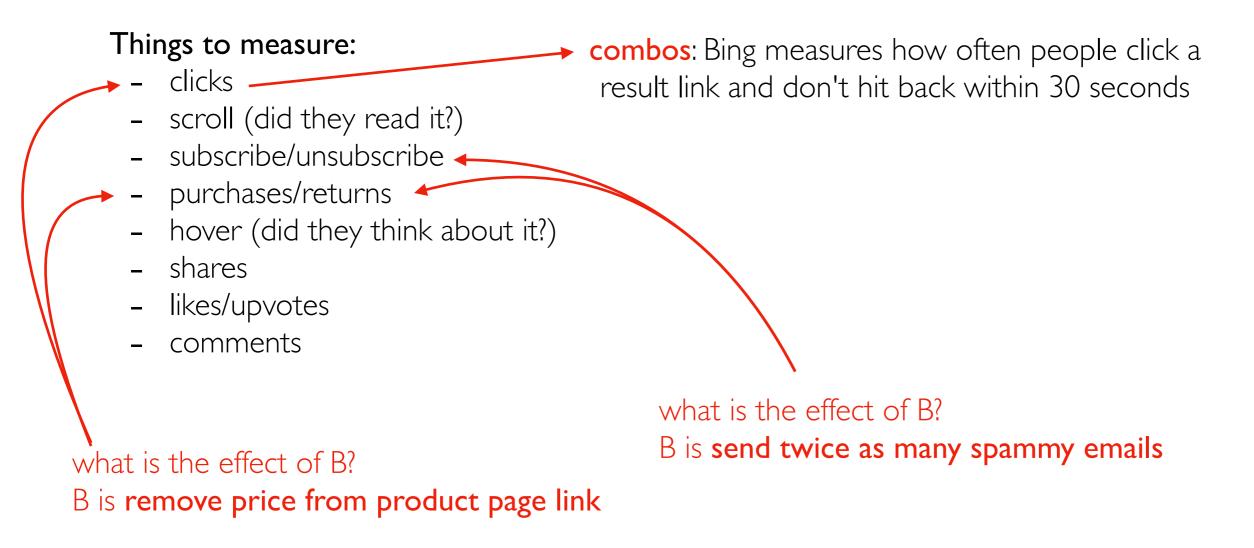
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combos: Bing measures how often people click a result link and don't hit back within 30 seconds

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B is send twice as many spammy emails



Things to measure:

- clicks
- scroll (did they read it?)
- subscribe/unsubscribe
- purchases/returns
- hover (did they think about it?)
- shares
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- comments

what is the effect of B?
B is remove price from product page link

combos: Bing measures how often people click a result link and don't hit back within 30 seconds

result link and don't hit back within 30 seconds

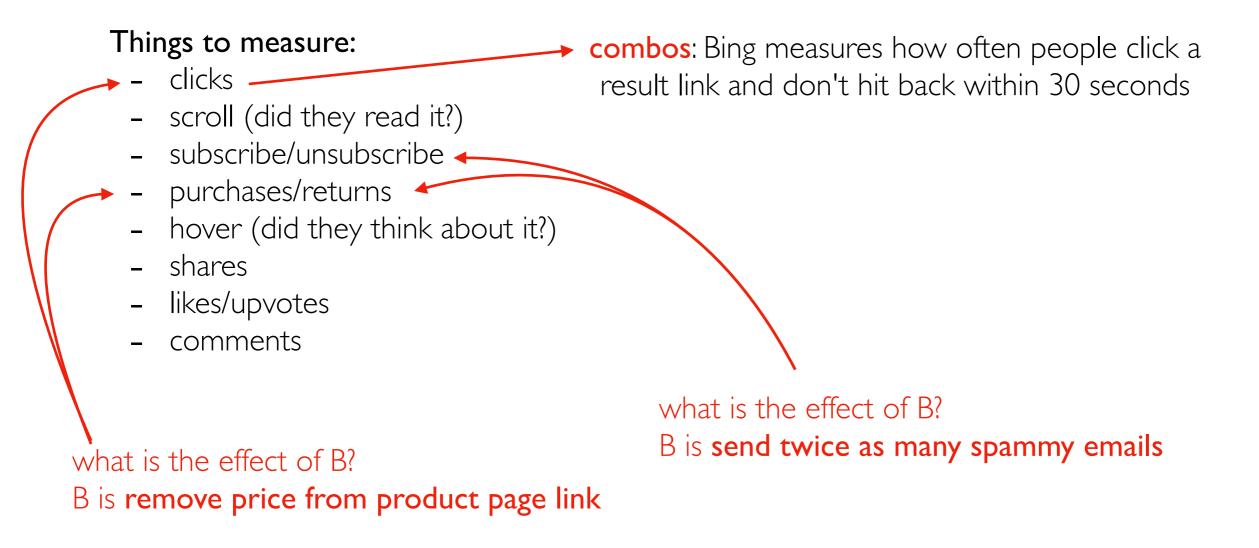
what is the effect of B?

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Lesson: it's easy to shift clicks

Lesson: it's hard to measure long-term effects (noisy!), so use common sense

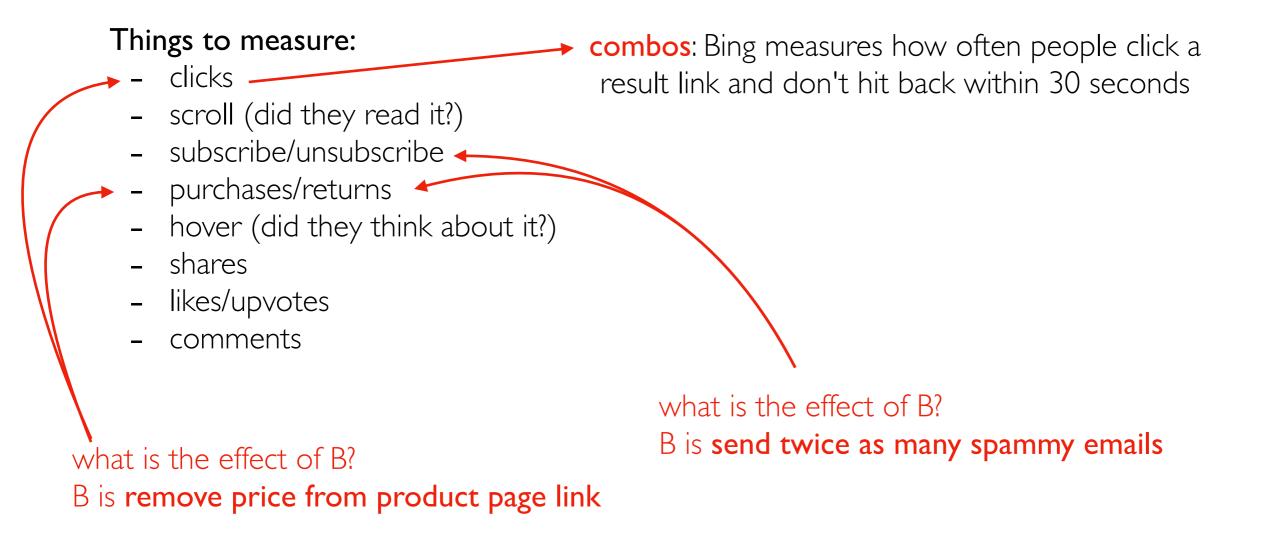
Metrics



Decide beforehand on one OEC metric: Overall Experiment Criterion

Bing has thousands of debug metrics, but only 4 OECs.

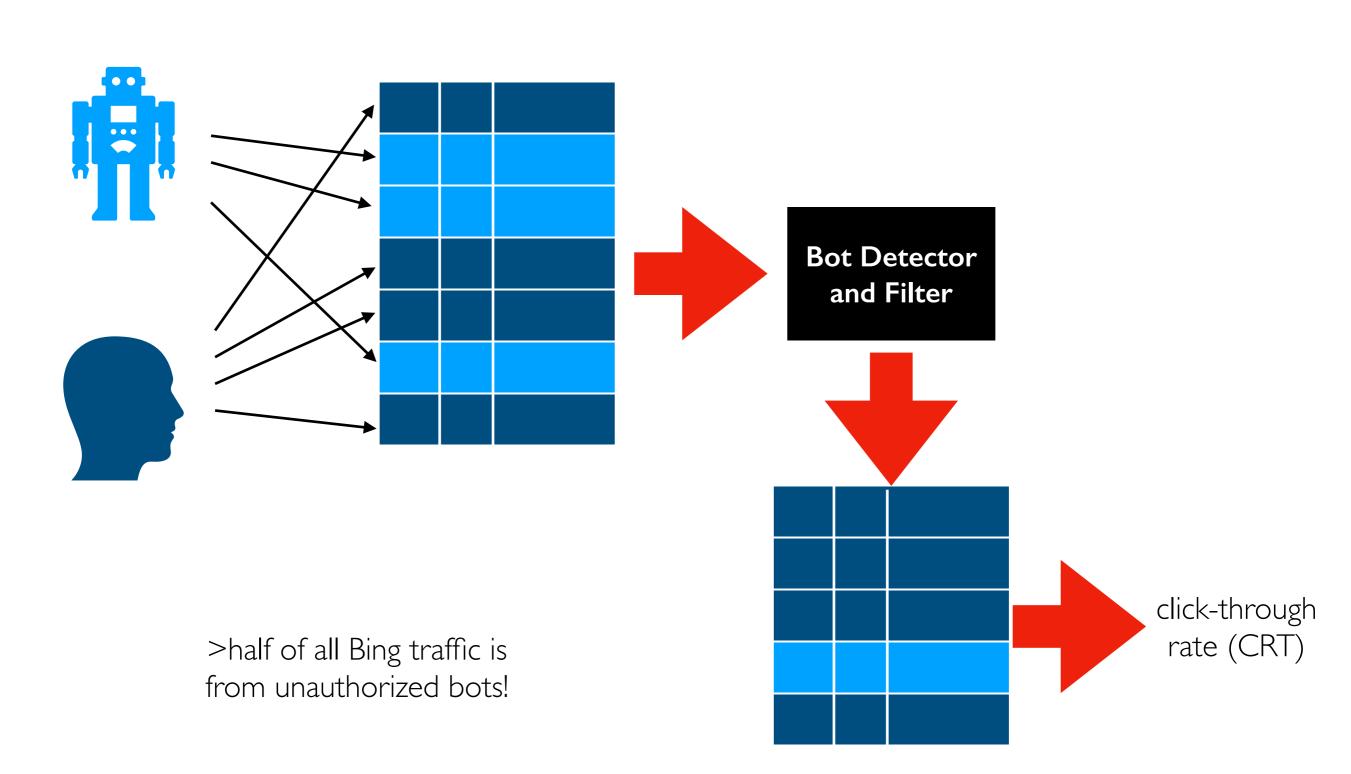
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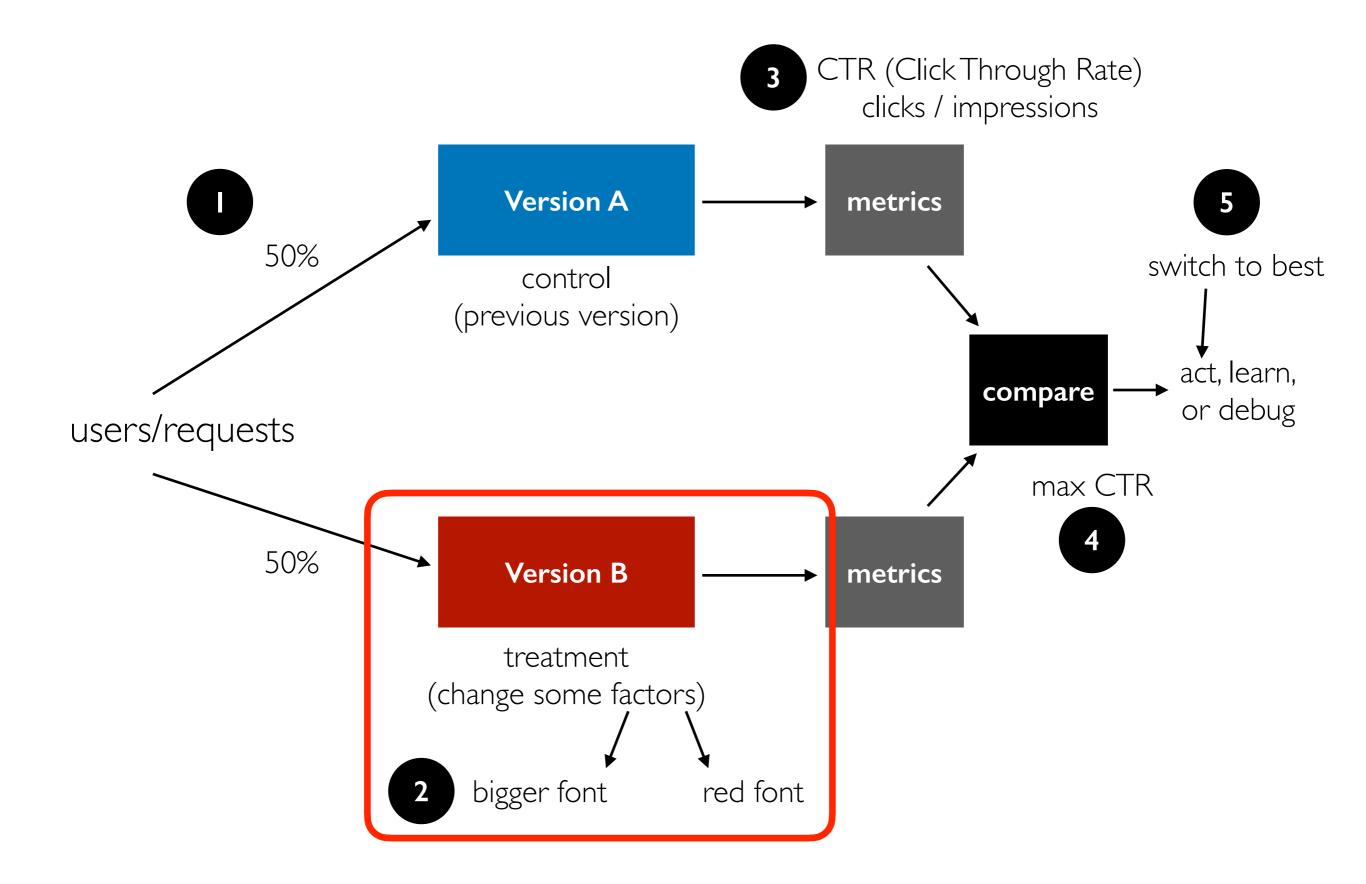
Decide beforehand on one OEC metric: Overall Experiment Criterion

- Bing has thousands of debug metrics, but only 4 OECs. Try to consider cost as well as benefit!
- As a rule of thumb, "if you make something bigger, more people will click on it" ~ Ron Kovani
- Making part of the site better could hurt other parts if you have a naive OEC

Metrics Should be on Uniformly Cleaned Data



Lecture Outline



Run two variants side by side: control (A) and treatment (B)

Treatment consists of one or more factors changed:

- wording
- slowdown
- changes "invisible" to user (e.g., updates)
- what else?

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- recommendation algorithm used
- sequence of steps necessary to make a purchase
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Lesson: don't be too attached to your work, be redundant and ready to throw things away

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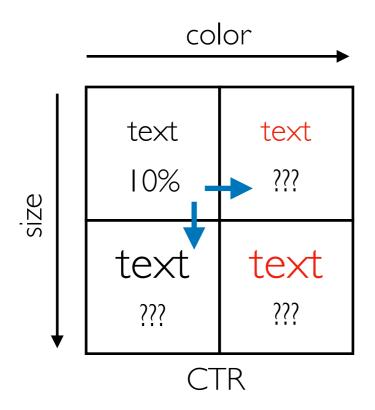
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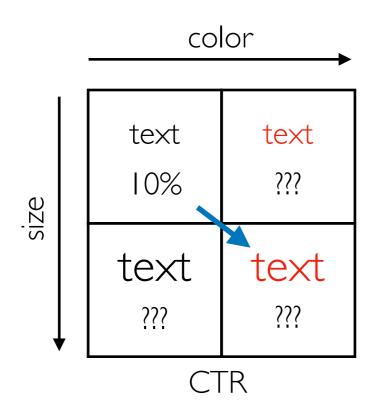
there's also plenty of low-hanging fruit!

"stop debating, it's easier to get the data" ~ Ron Kohavi



Option I: OFAT (one factor at a time)

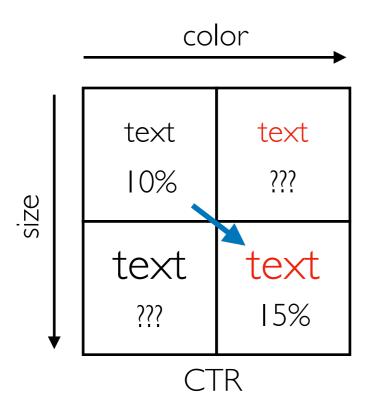
Hypothesis: large red font will be better



Option I: OFAT (one factor at a time)

Option 2: introduce two factors at once

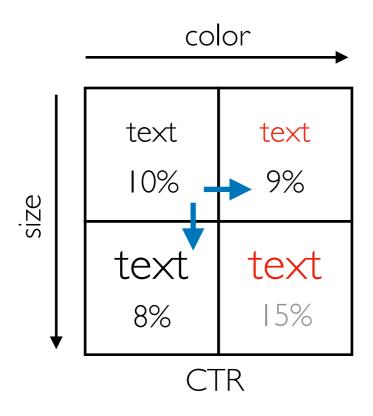
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Option I: OFAT (one factor at a time)

Option 2: introduce two factors at once can choose a good design, but didn't learn what factors are important



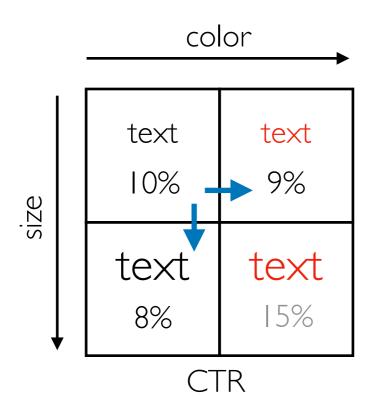
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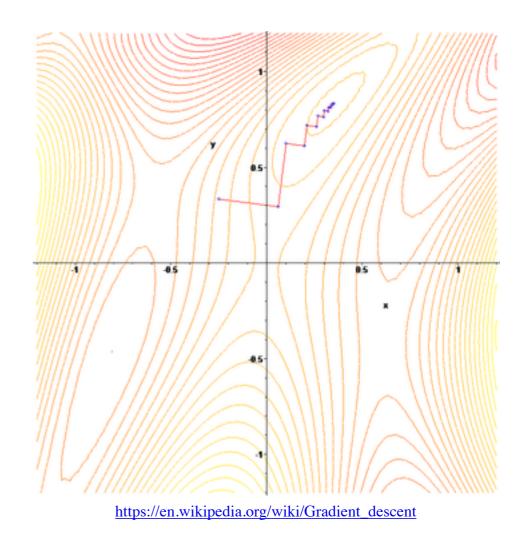
can usually learn more, but will

never exploit factor interactions

Option 2: introduce two factors at once can choose a good design, but didn't learn what factors are important

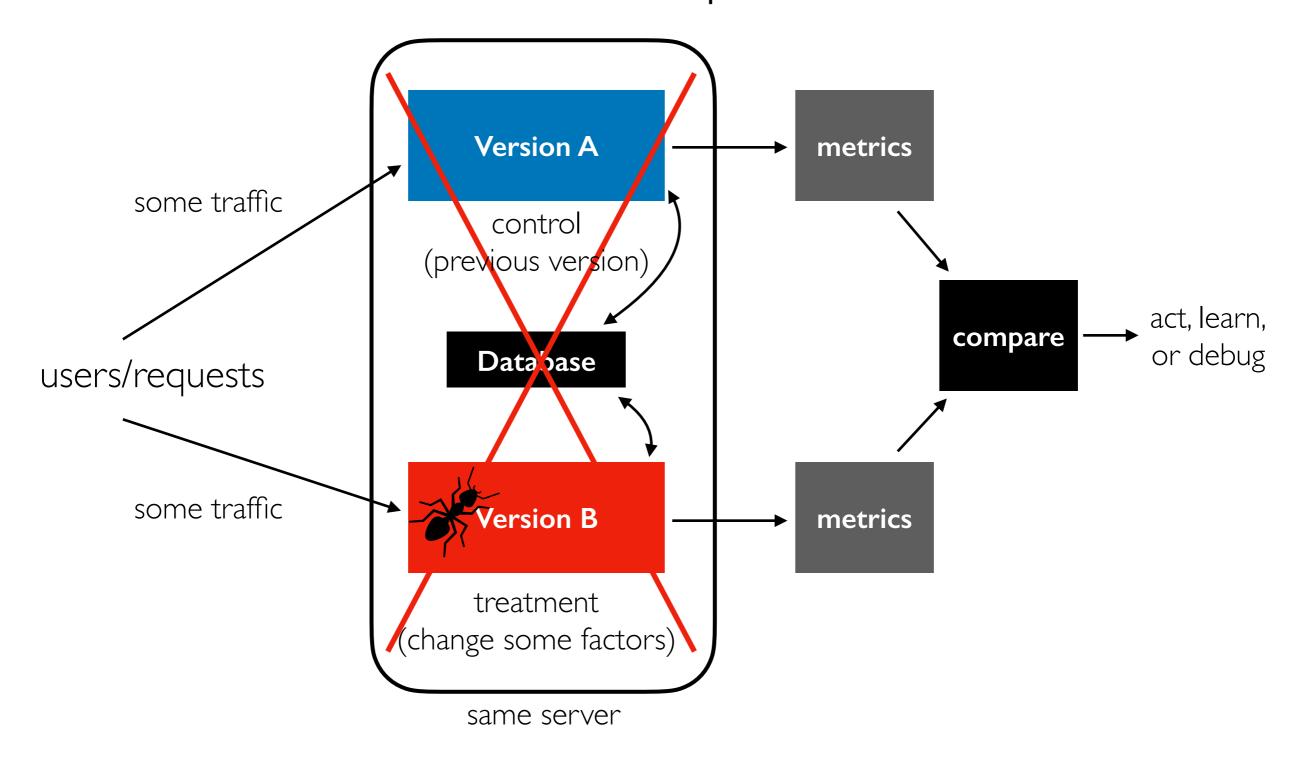


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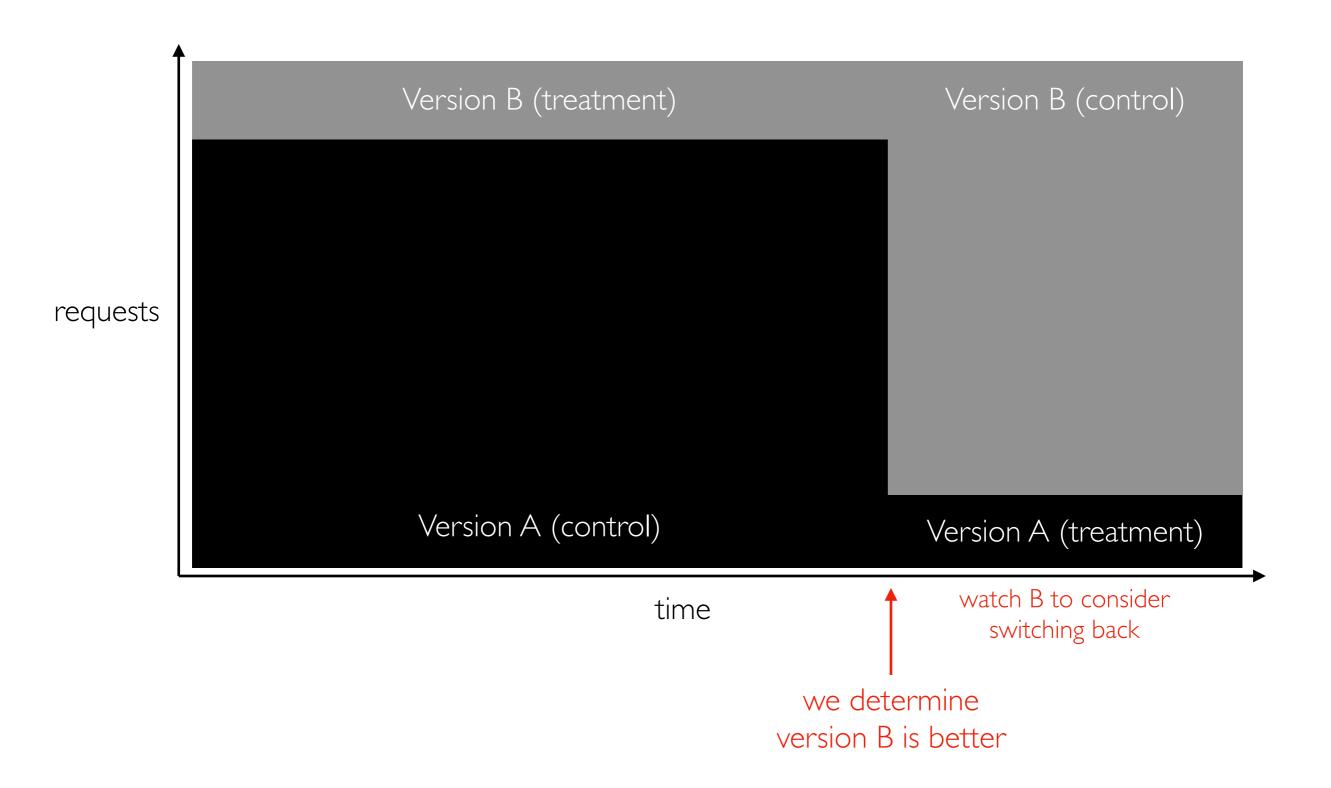
Hill climbing: imagine you're trying to find a peak (representing higher CTR). Taking small steps in the steepest direction is usually best, but not if you reach a local peak/optimimum

Control/Treatment Disruptions

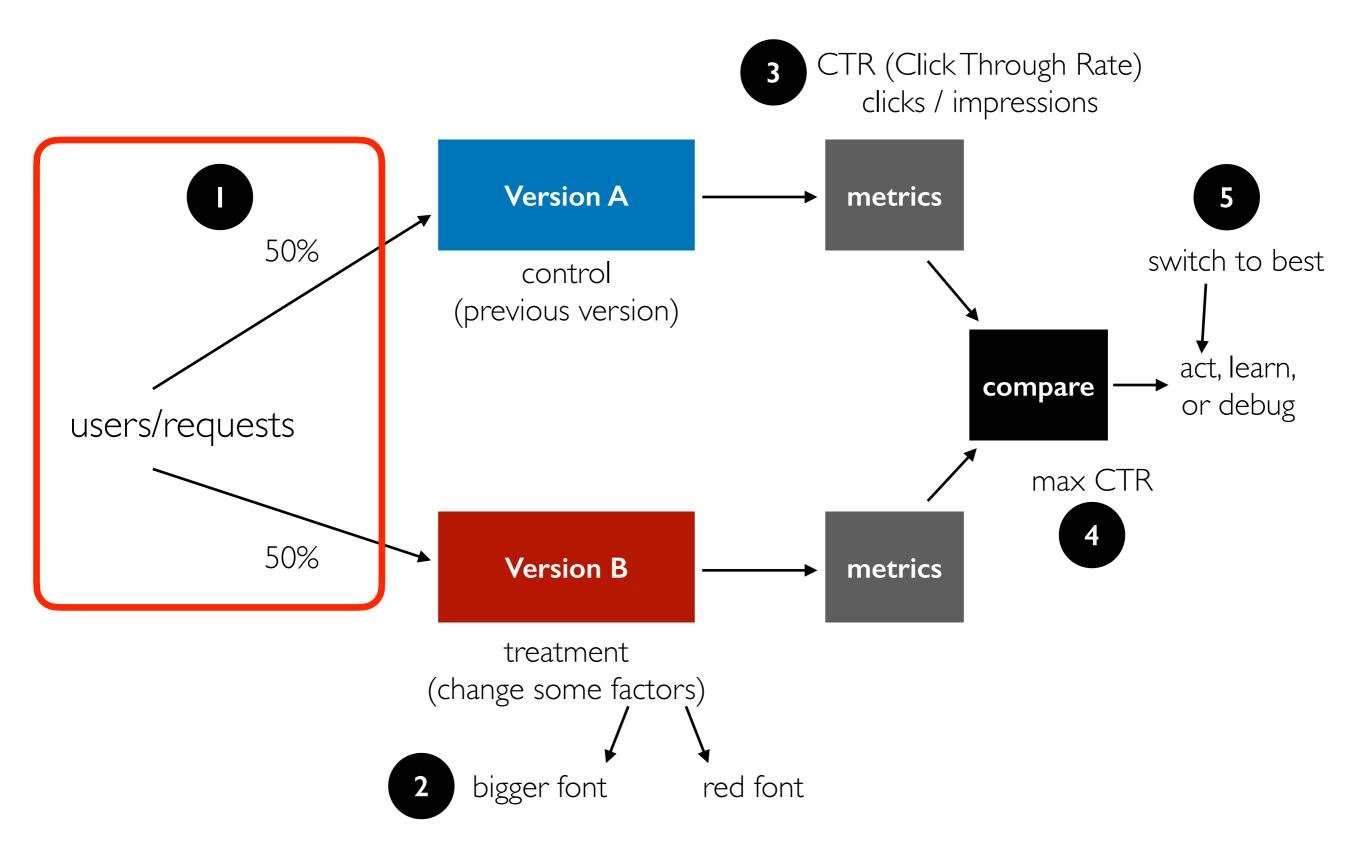


Different variants may save databases/servers, affecting performance of both. Bugs crashing the server will be especially bad! Metrics won't show the true blame.

What if the real factor is **novelty**?

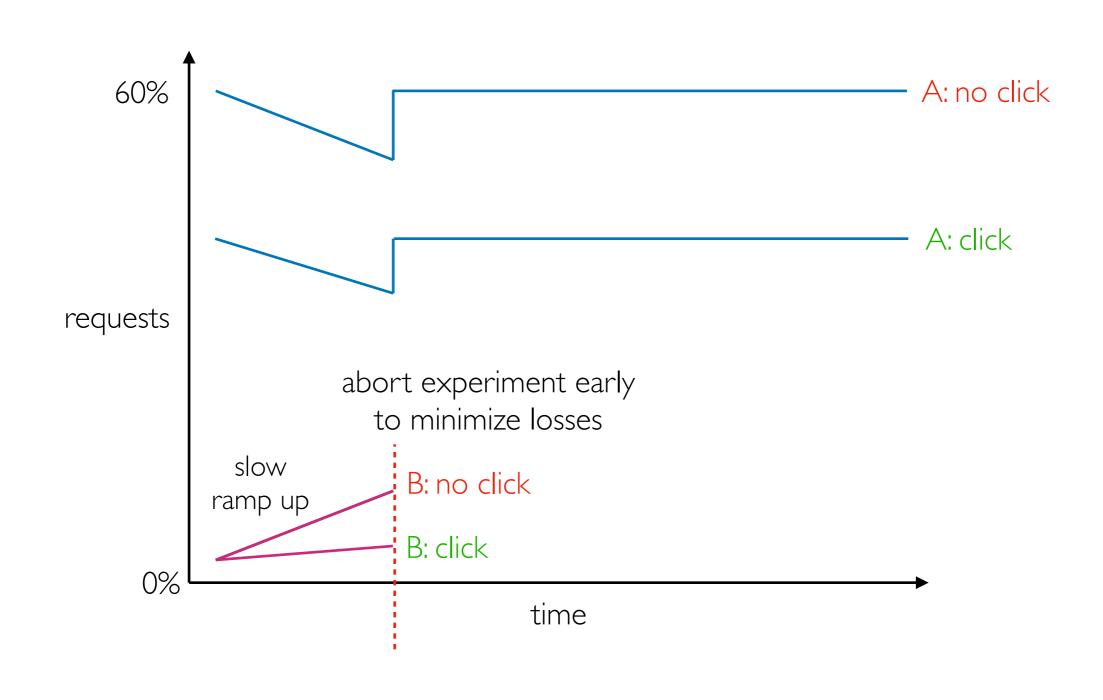


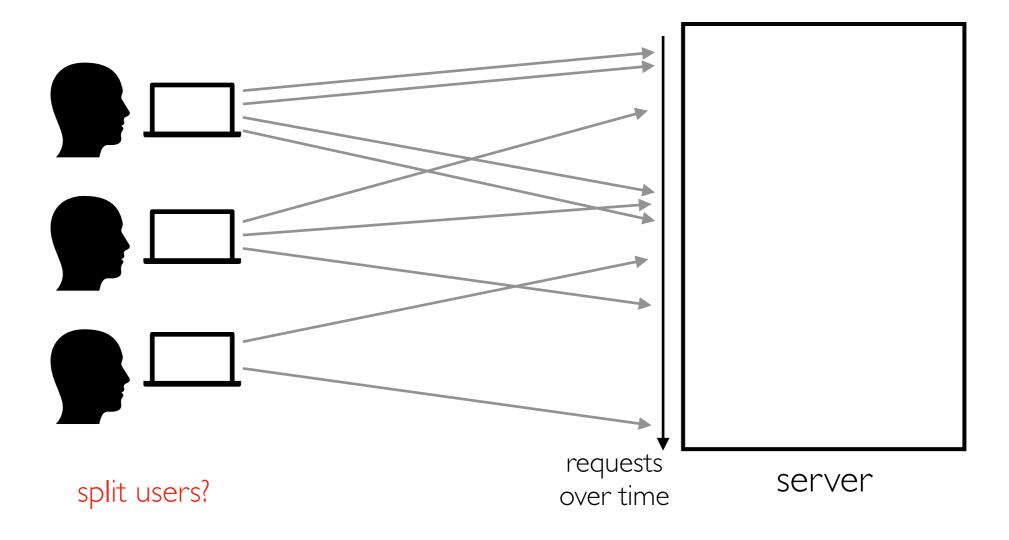
Lecture Outline



What to split

Don't go straight to 50/50!



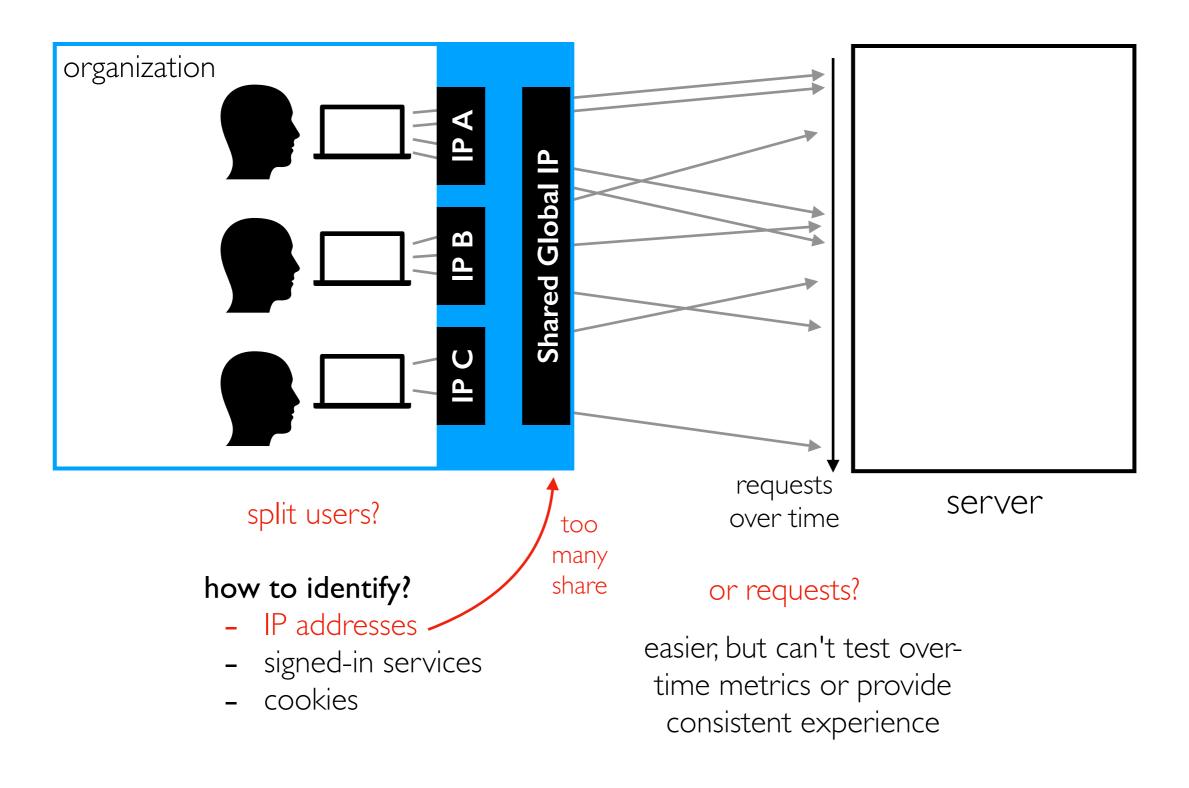


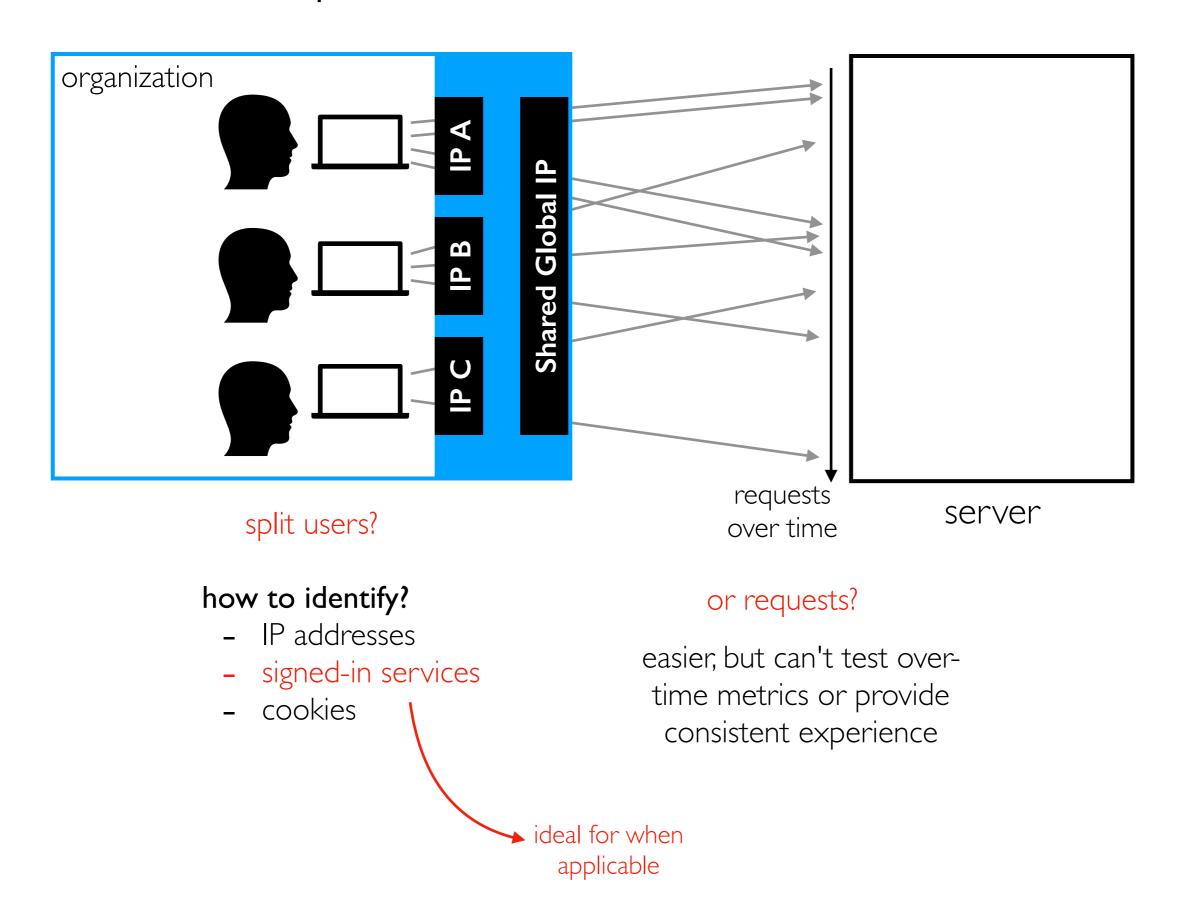
how to identify?

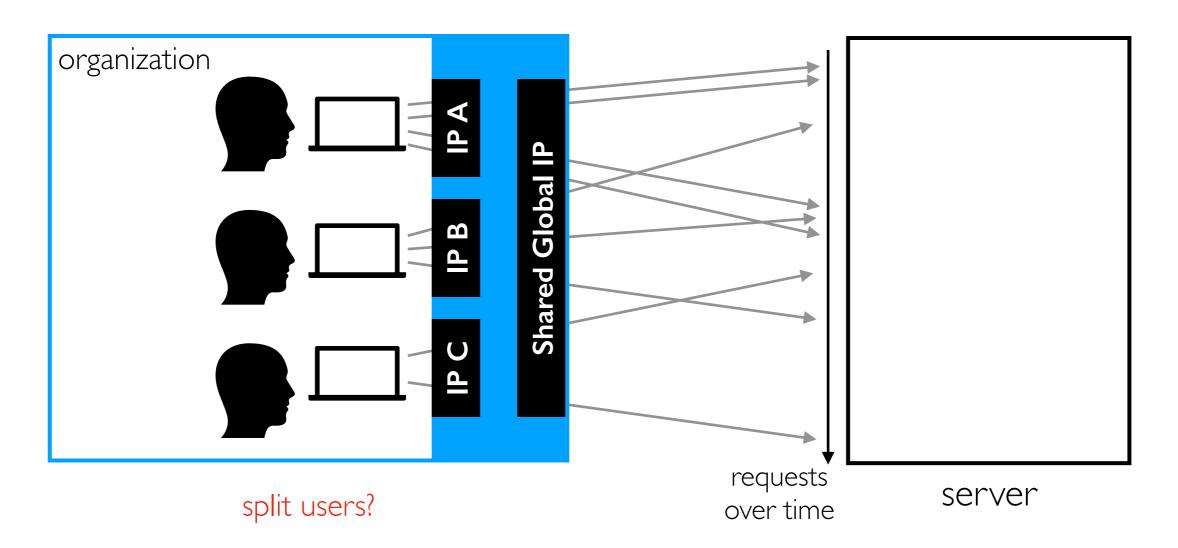
- IP addresses
- signed-in services
- cookies

or requests?

easier, but can't test overtime metrics or provide consistent experience







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or requests?

easier, but can't test overtime metrics or provide consistent experience

Cookies

Cookies are info that sites ask browsers to store locally and upload later.

```
from flask import request, Response, Flask
app = Flask(name)
                                           dict of cookies
@app.route('/')
def index():
    print(request.cookies)
    user_id = request.cookies.get("user", None)
    if user id == None:
        user id = new id()
    resp = Response("hello")
    resp.set_cookie("user", user_id)
    return resp
                      key
                              value
def new id():
    import time
                             #TODO: get better identifiers
    return str(time.time())
app.run(host="0.0.0.0")
```

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    return resp
                      key
                               value
def new id():
    import time
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    return str(time.time())
app.run(host="0.0.0.0")
                                     lncognito
```

More accurace than IP, but cookie churn, incognito mode, and local laws may limit...

Summary

Goals

- make decisions, learn, debug

Comparisons

- significance testing

Metrics

- simple or combos
- clean uniformly
- choose OEC up front
- think long-term

Version A control (previous version) users/requests treatment (change some factors) metrics metrics metrics act, learn, or debug

Treatments

- one or more factors
- factors may require a lot of coding/design work!
- OFAT usually best for learning
- check the novelty factor with a flipped A/B test after decision

Splitting Traffic

- ramp up slowly
- split requests or users (how to distinguish?)