A/B Testing

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 Credits: these slides borrow heavily from examples and figures from Ron Kohavi's presentations on A/B testing at Microsoft (available online)

Introduction

- Systems (e.g., search systems) are always trying to improve
- Basic question: If a specific change is introduced, will it improve key metrics?
- Metrics: measures that are believed to be correlated with the quality of the user experience
- Metrics are often things we want to minimize or maximize
- Examples?

A/B Testing

- Experiments where different populations of users are exposed to different versions of the system for a period of time
- Control group: group of users exposed to the "normal" or "baseline" version of the system
- Experimental group: group of users exposed to the experimental version of the system
- More often A/B/C/D/E... testing
- Search companies can have about 15 different A/B tests happening at once
- $5^{15} = 30,517,578,125$

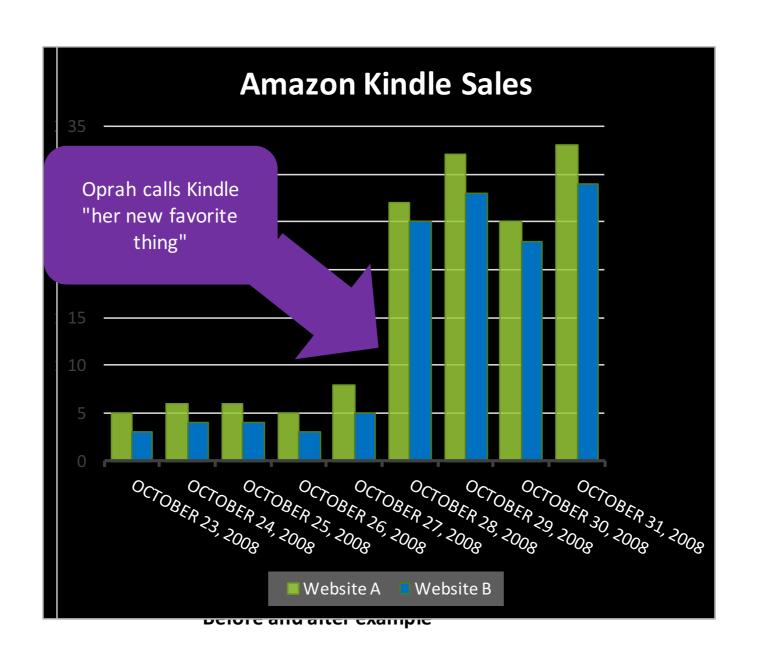
The Alternative

- Make the change and measure the same metrics.
- Why is this a bad idea?

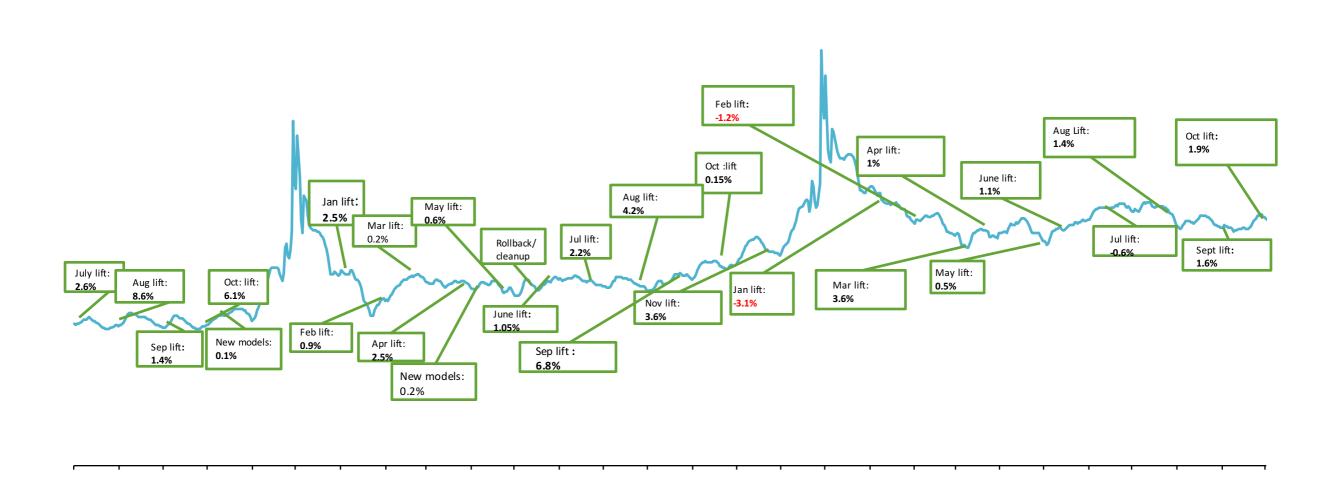
The Alternative

- Make the change and measure the same metrics.
- Why is this a bad idea?
 - 1. Temporal changes
 - 2. Good features lead to incremental improvements
 - 3. It's difficult to assess the value of ideas

Temporal Changes



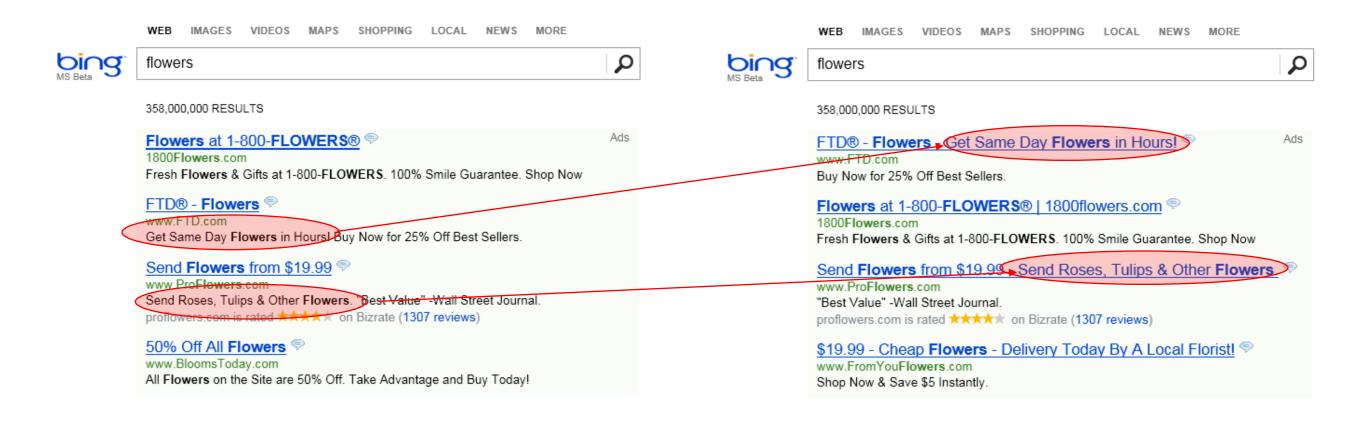
Temporal Changes + Incremental Improvements



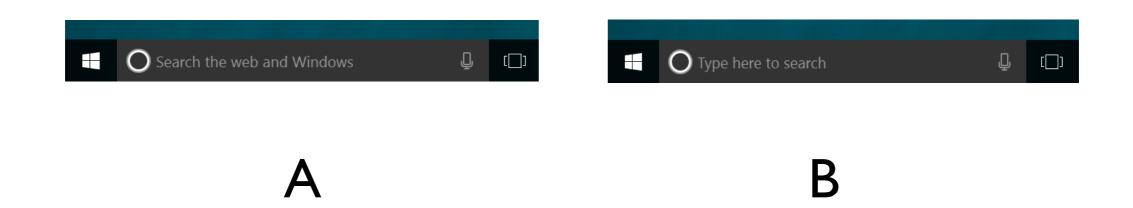
Predicting the value of new features

- 1/3 of ideas improve the intended metric(s)
- 1/3 of ideas have no effect
- 1/3 of ideas degrade the intended metric(s)

Predicting the value of new features

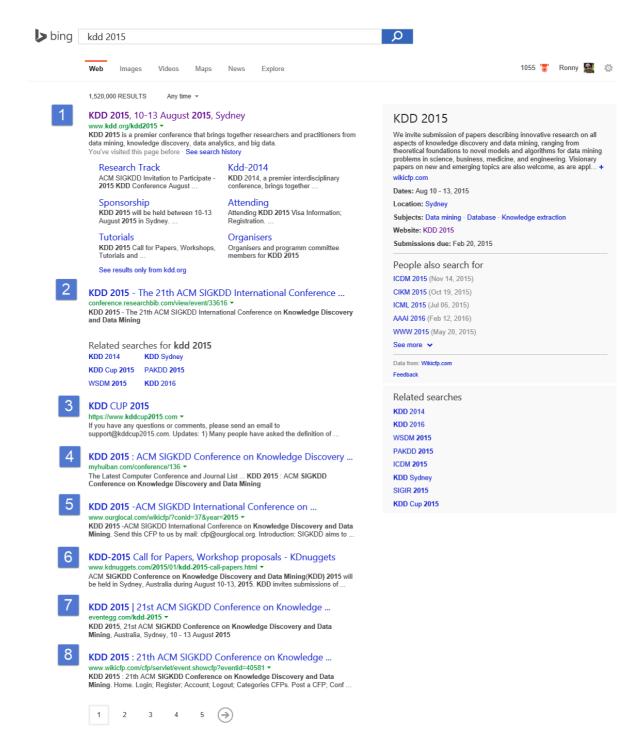


(1) Predicting the value of new features



- Overall Evaluation Criterion: no. of searches
- A > B, A < B, or A = B?

(2) Predicting the value of new features



(2) Predicting the value of new features

10 search results

8 search results

A

B

- Overall Evaluation Criterion: clickthrough rate 1st SERP per query
- A > B, A < B, or A = B?

(3) Predicting the value of new features

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Get Your Free Online Quote Today!

Get a Quote Find Discounts An Allstate Company Compare Rates

A

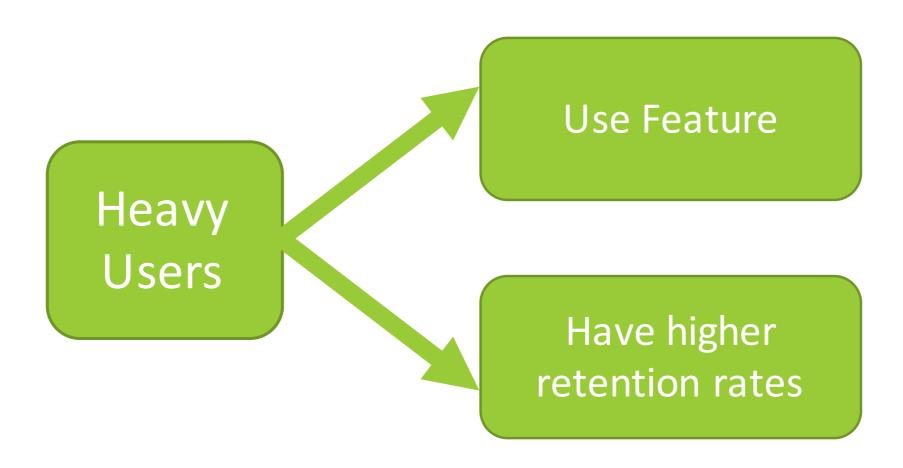
- Overall Evaluation Criterion: revenue
- 4 A ads for every 3 B ads
- A > B, A < B, or A = B?

Challenges in A/B Testing

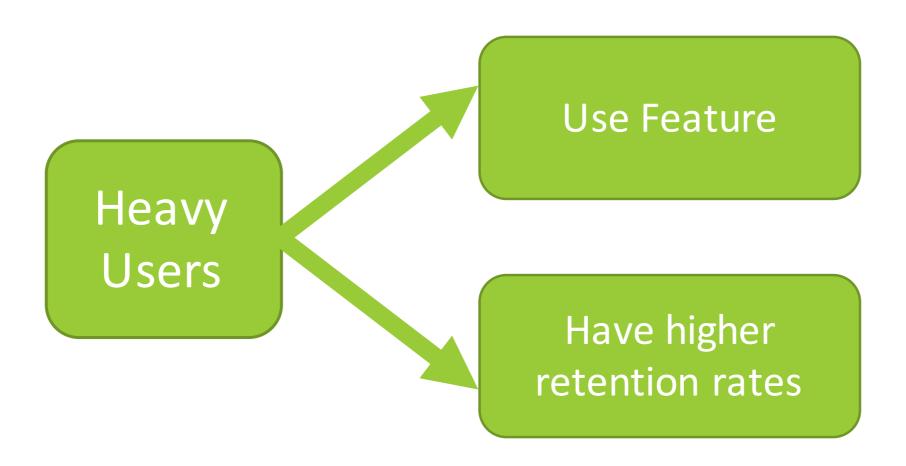
- Correlation does not imply causation
- Understanding how short-term metrics (measured during A/B tests) lead to long-term improvements in user experience and/or revenue
- Using the wrong metric
- Unexpected effects on important metrics
- Making claims not exactly tested
- Bugs in the experimental infrastructure
- Using sound statistical methods
- Hurting the user experience

- Umbrellas cause rain
- People with small hands live longer
- A new feature (e.g., a new advanced search tool) increases retention rate

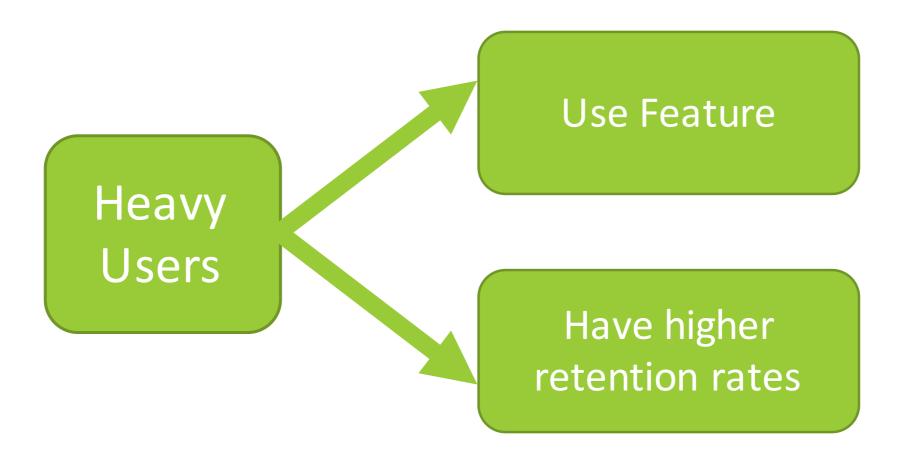
 Particularly important for understanding the impact of system features that are used more by certain types of users than others



What are features used more by <u>heavy</u> users?



What are features used more by <u>new</u> users?



Challenges in A/B Testing

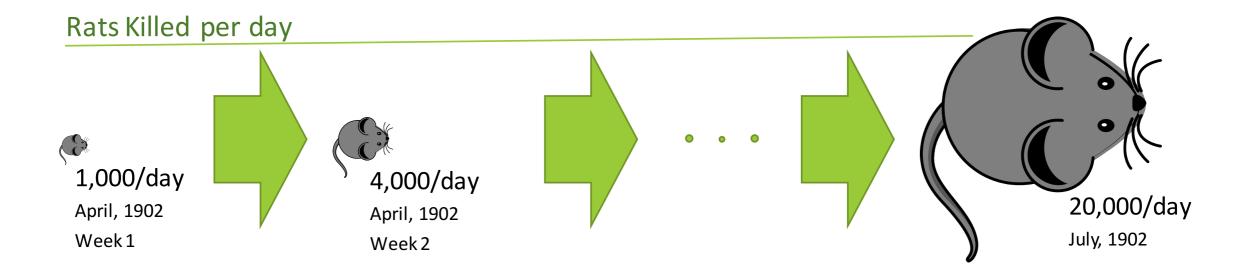
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Short-term vs. Long-term Metrics

- An increase in ad clicks suggests an increase in revenue
- Showing lots of ads (often) hurts the user experience and decreases retention (i.e., long-term ad-click revenue)

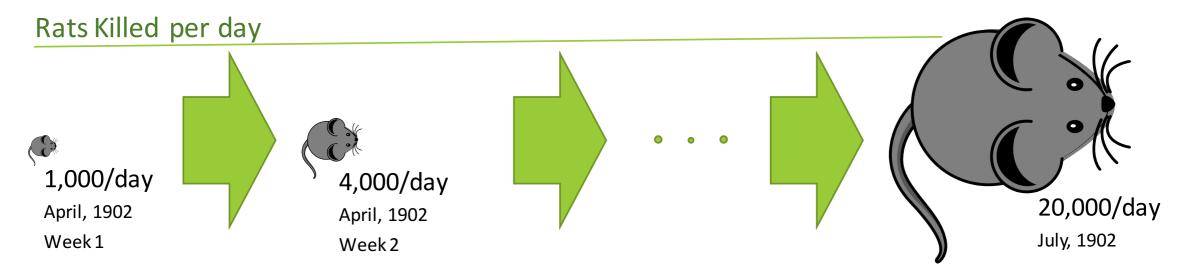
Using the wrong metric

Hanoi's French Quarter rat problem in 1902



Using the wrong metric

Hanoi's French Quarter rat problem in 1902



- What you do not measure, does not improve.
- Goodhart's law: "when a measure becomes a target, it ceases to be a good measure"

Unexpected Effects on Important Metrics

- Example: a hyperlink on the SERP was changed to open on a new browser tab.
- It increased avg. SERP load time by 8.32%
- Why?

thesitewizard.com

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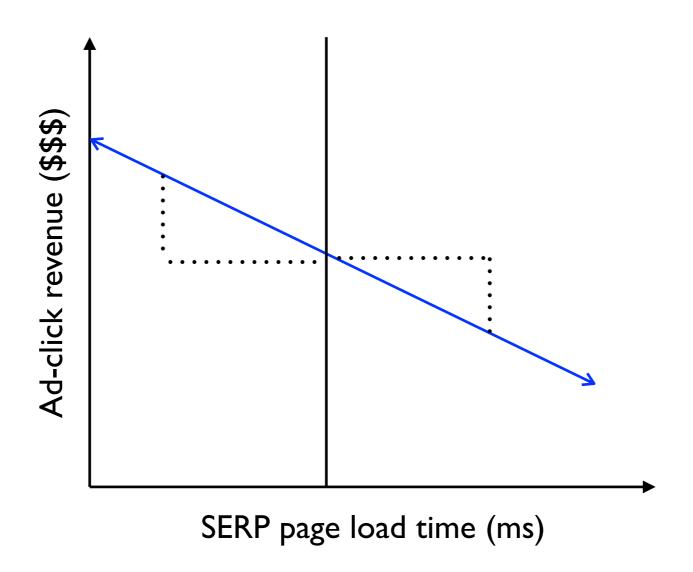
Making Untested Claims

- Question: What is the effect of SERP load-time on adclick revenue?
- Artificially <u>increase</u> SERP load-time and measure <u>decrease</u> in ad-click revenue
- Make the claim that <u>decreasing</u> the SERP load-time will have a comparable <u>increase</u> in ad-click revenue
- What's wrong with this?

Making Untested Claims

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- What's wrong with this?
- Assumes (bi-directional) linear relationship

Making Untested Claims



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Bugs in the Experimental Infrastructure



- User sampling + measurement + statistics
- How can we debug this infrastructure without opening the "black box"?

Bugs in the Experimental Infrastructure



- Run lots of A/A tests (no differences between experimental and control conditions)
- How often should we observe a p-value of 0.05 or less?

Sound Statistical Methods



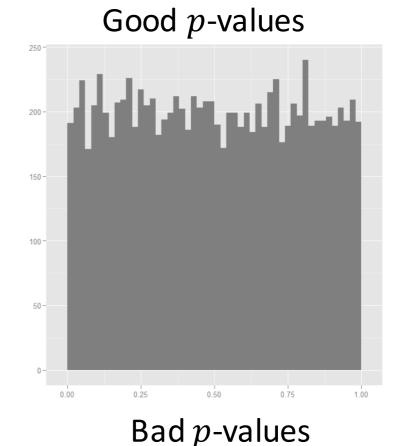
- Even when there is no difference between the two systems, it is still possible to observe a *p*-value of less than 0.05
- Why?

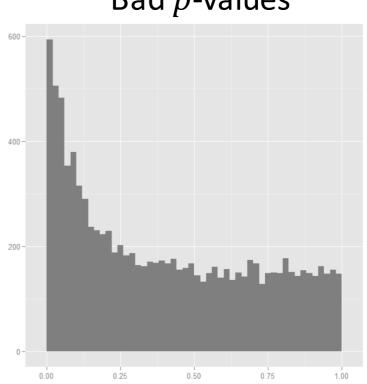
Sound Statistical Methods

• By definition, the *p*-value is the probability of the <u>observed difference in means</u> (or a more extreme difference) under the null hypothesis!

A/A Testing

- Run lots of A/A tests (no differences between experimental and control conditions)
- We should only observe *p*-values of 0.05 or less about 5% of the time
- The p-value distribution should be uniform rather than skewed to low or high values





Challenges in A/B Testing

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Causes of Type I Errors (False Positives)

- Running the same A/B test many times until we observe a significant difference
- Using 100+ metrics and focusing on the ones that are significant
- Running an experiment for as long as it takes to reach significance
- Running an experiment and stopping early because we reached significance

Causes of Type I Errors (False Positives)

 Bonferroni correction: multiplying the *p*-value by the number of comparisons

Hurting the User Experience

- Less manual monitoring of experiments
- Buggy features or bad ideas
- Interactions between concurrent experiments: the whole is less than the sum of its parts

Cautionary Steps: Starting Small

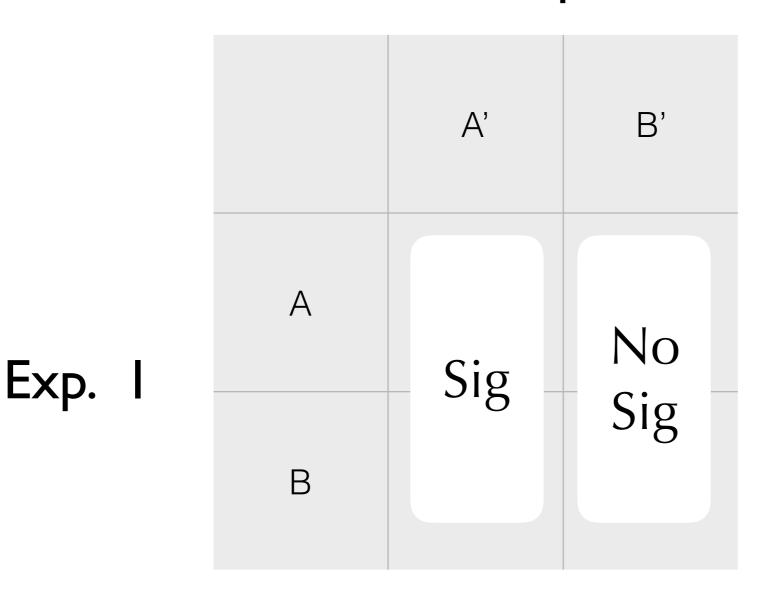
- Starting internally (within the company)
- Starting with only a few users
- Starting with only partial exposure (1/10 queries)

Cautionary Steps: Different types of Metrics

- Data quality metrics: ensure that the feature was implemented correctly
- Overall evaluation criteria: single metric that measures improvement in user experience (e.g., number of satisfied clicks)
- Guardrail metrics: metrics used to shutdown an experiment (e.g., queries with no clicks)
- Local metrics: metrics that measure what the user is doing less of (because of the new feature)

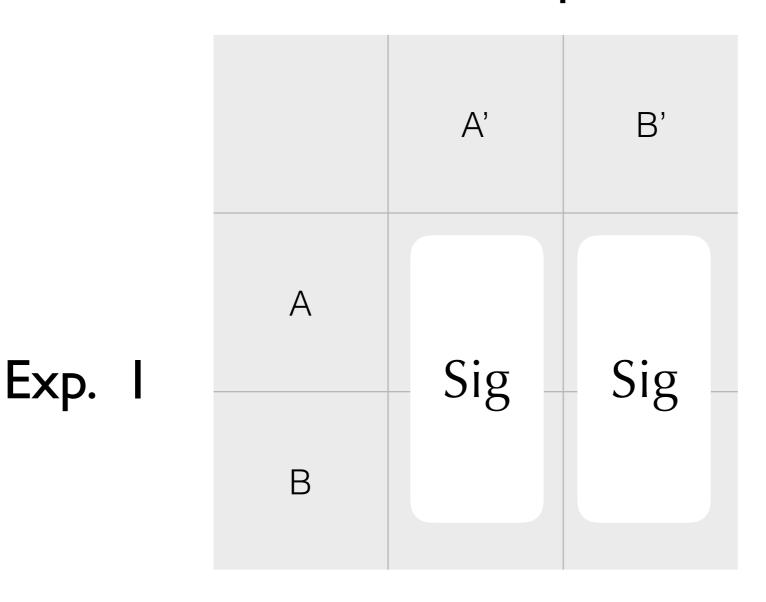
Cautionary Steps: Measuring interactions

Exp. 2

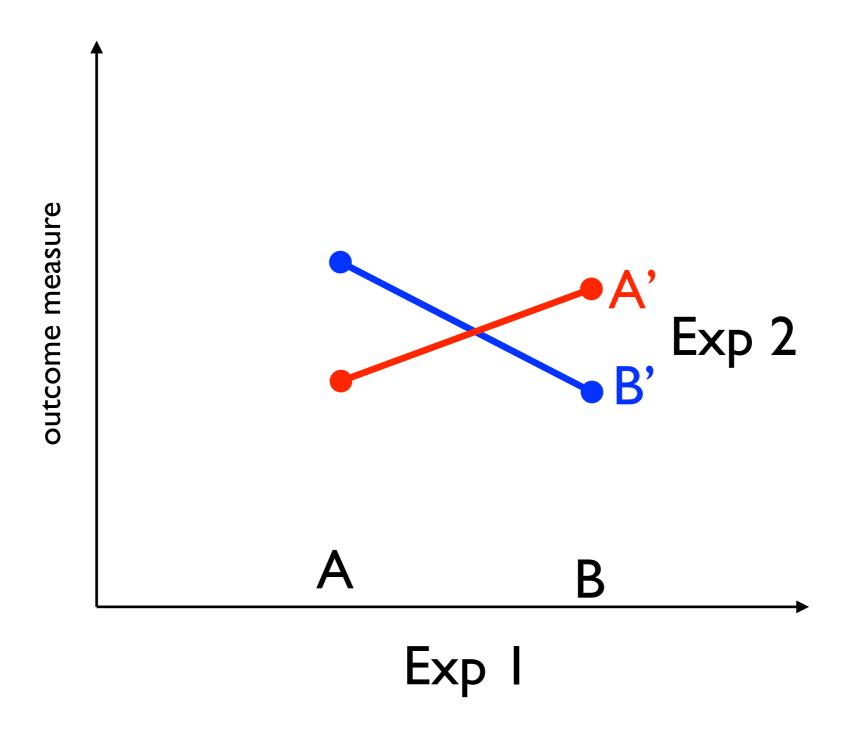


Cautionary Steps: Measuring interactions

Exp. 2



Cautionary Steps: Measuring interactions



Ethical Considerations

- System development is influenced by the majority
- Certain communities may be under-represented in the data
- While there is an "average user", there is also high variance (nobody is close to the average)
- Metrics used in A/B tests are <u>crude measures</u> of "user experience"
- Users may need to experience extreme differences to show (positive or negative) changes in behavior
- A/B tests are done without considering whether the user is in a vulnerable state

Challenges in A/B Testing

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