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?

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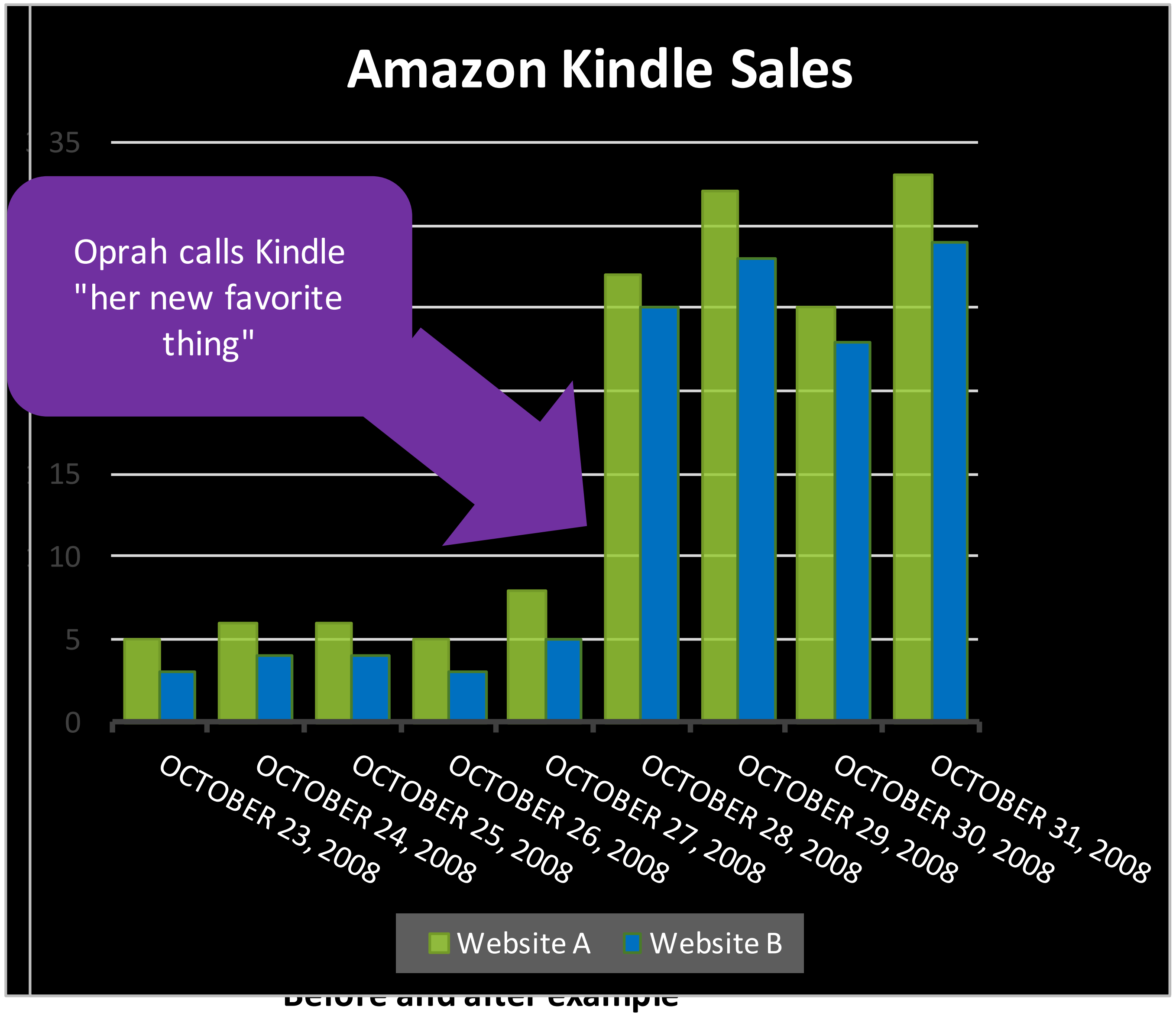
- Make the change and measure the same metrics.
- Why is this a bad idea?

1. Temporal changes
2. Good features lead to <u>incremental</u> improvements
3. It's difficult to assess the value of ideas

Temporal Changes



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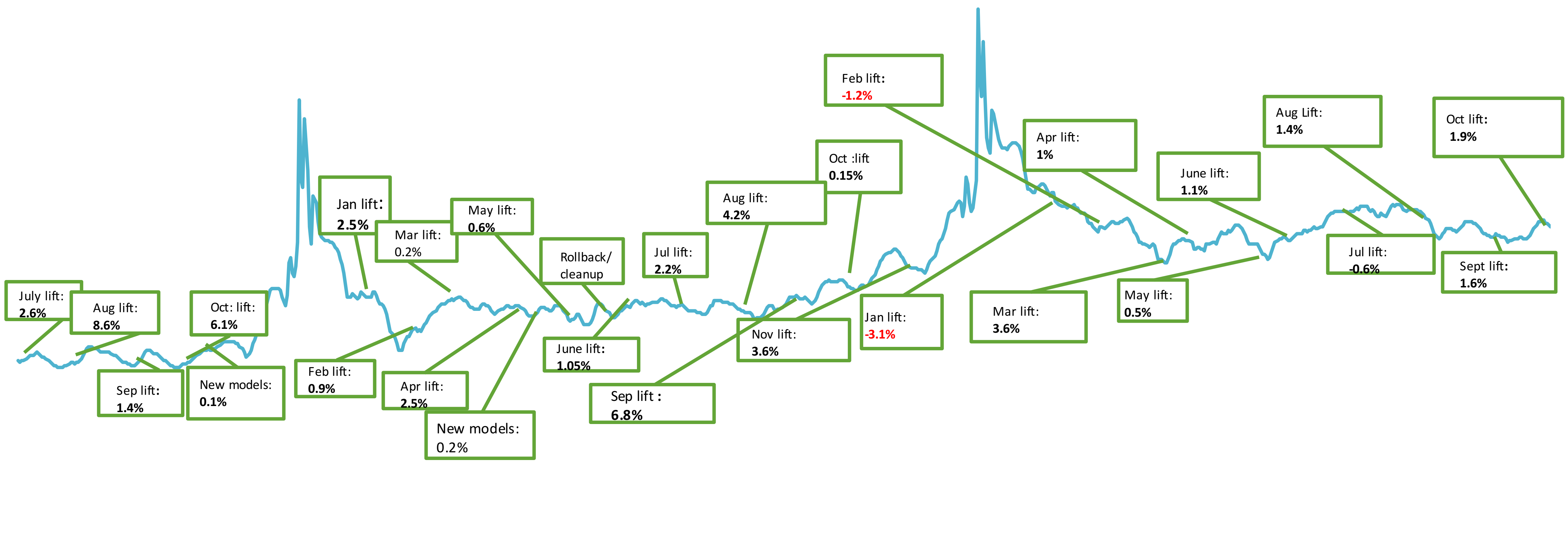
Temporal Changes + Incremental Improvements



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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)

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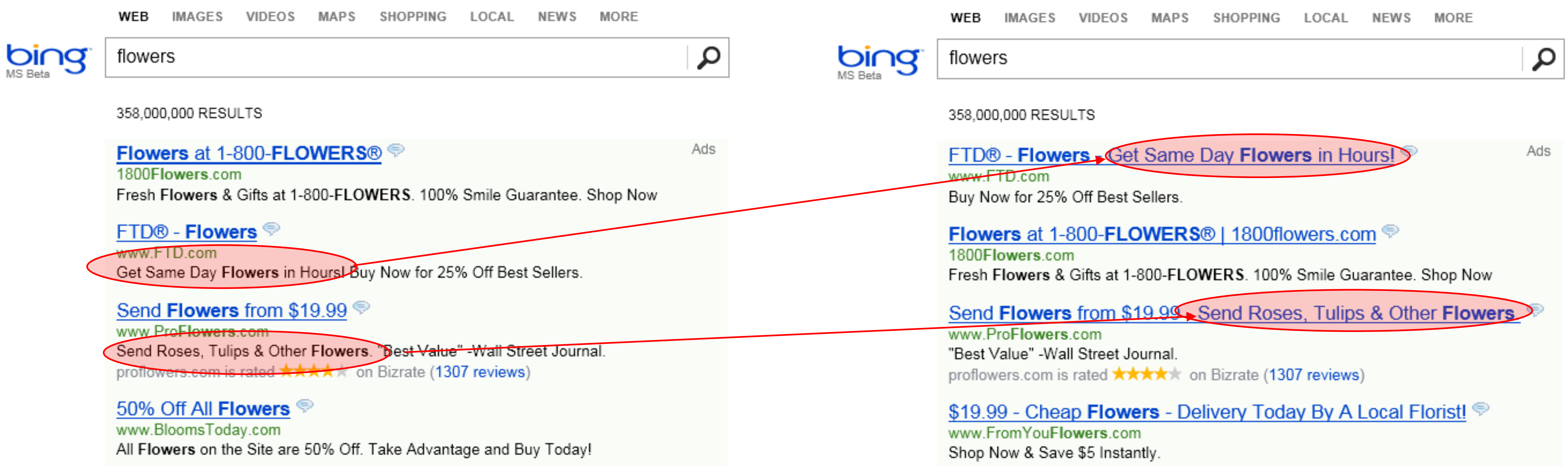
Predicting the value of new features



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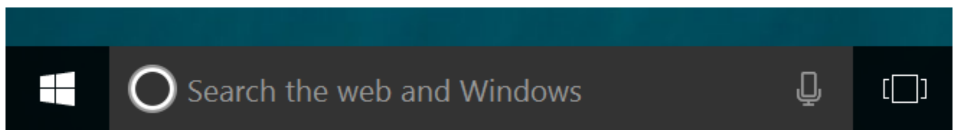
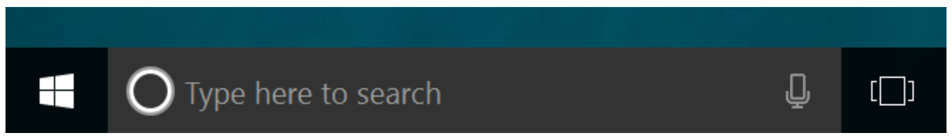
(1) Predicting the value of new features



A



B

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

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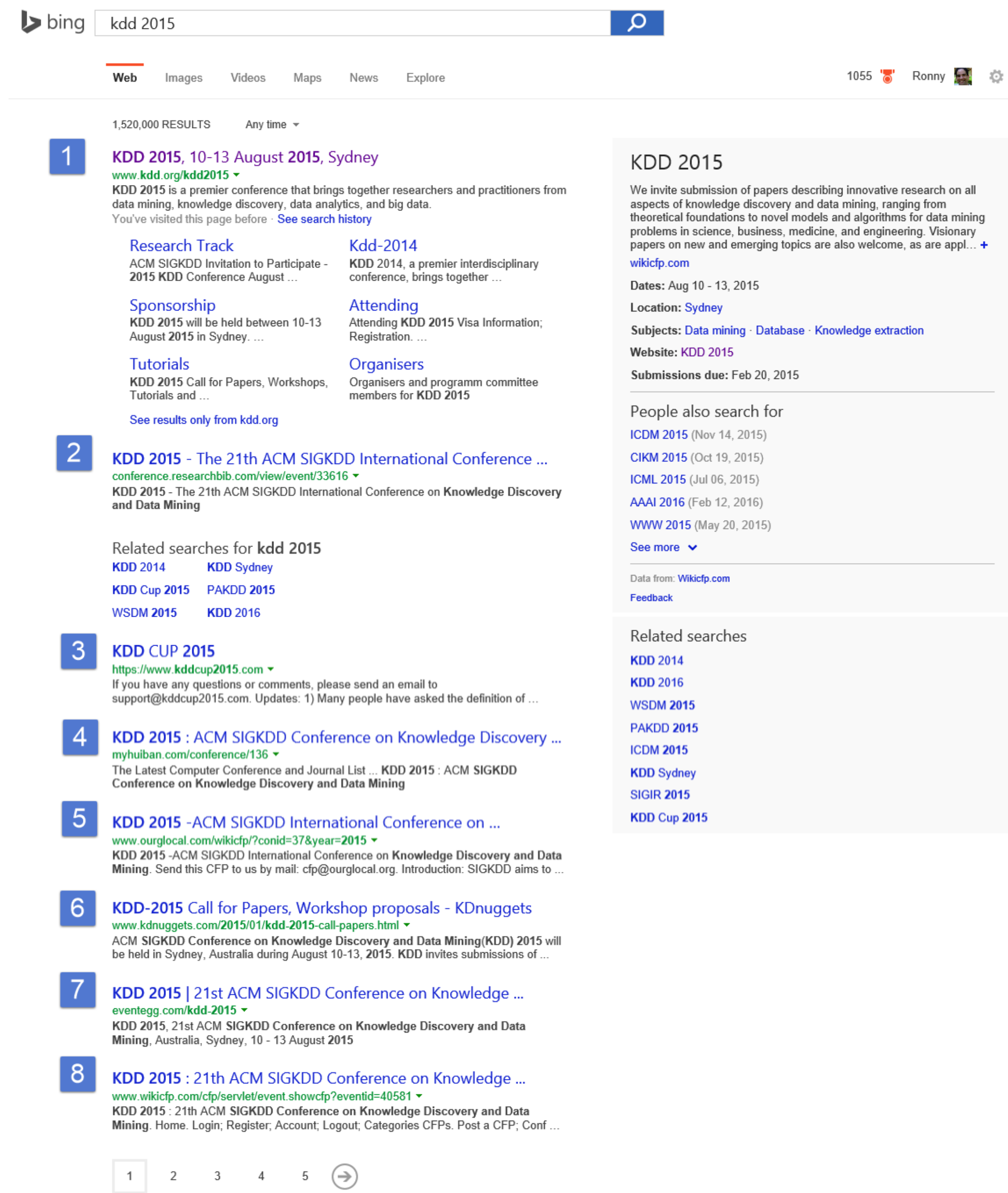
(2) Predicting the value of new features



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(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?

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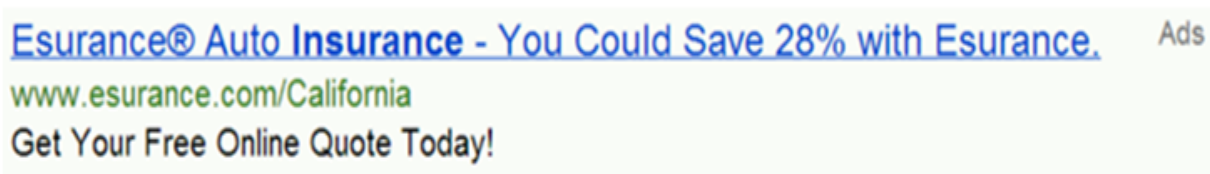
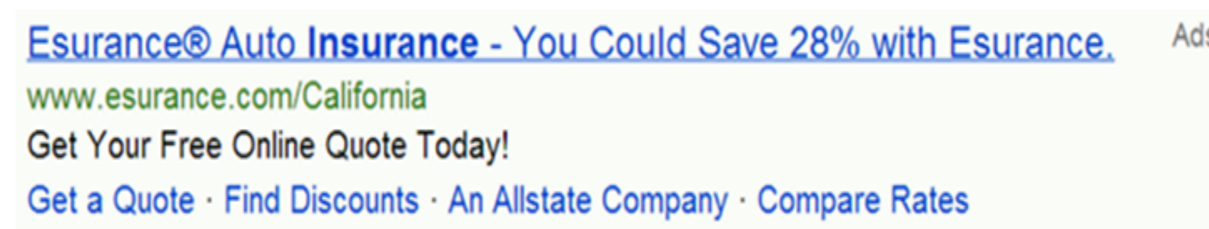
(3) Predicting the value of new features



A



B

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

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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

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Correlation does not Imply Causation

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

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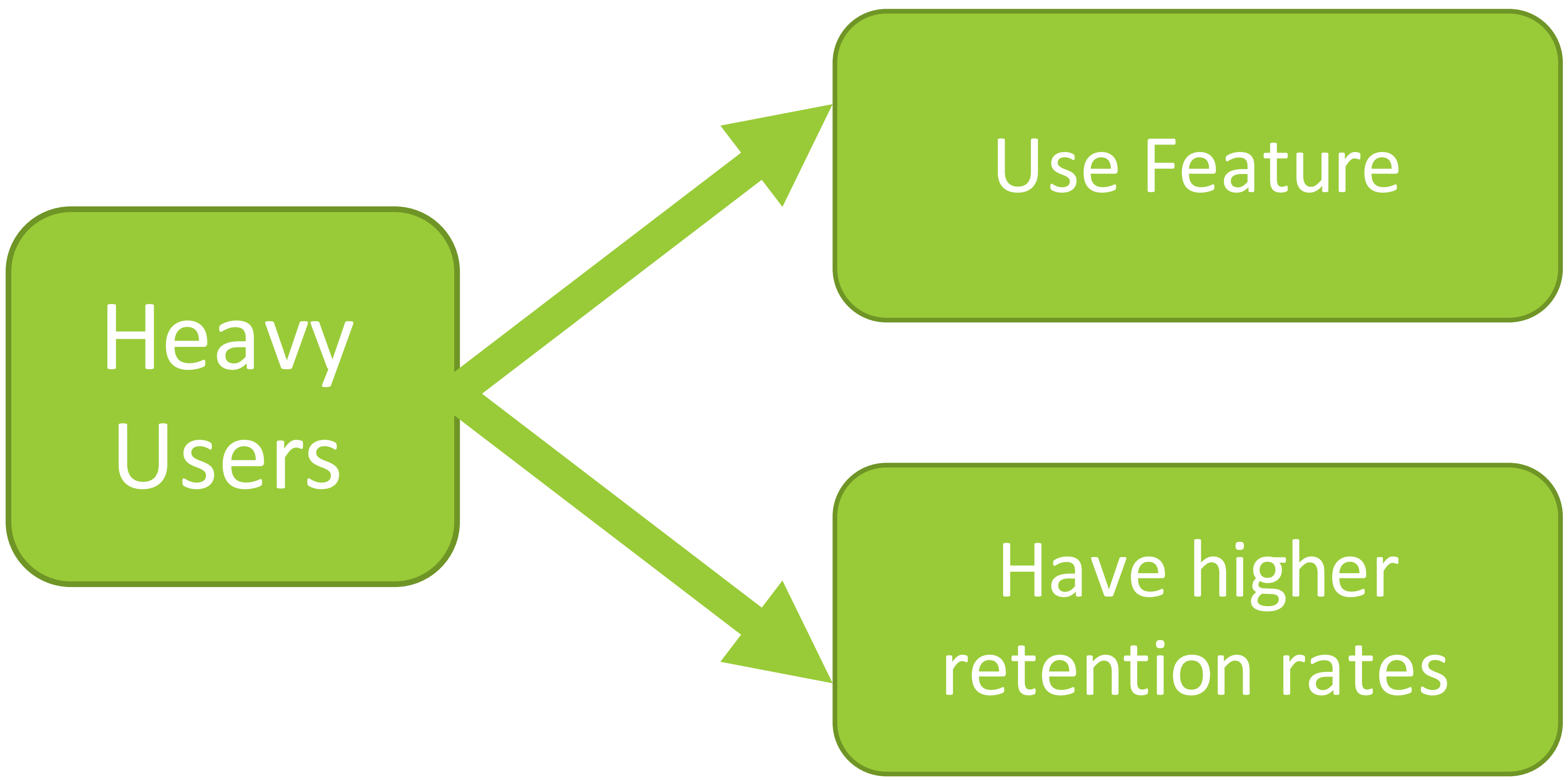
Correlation does not Imply Causation

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



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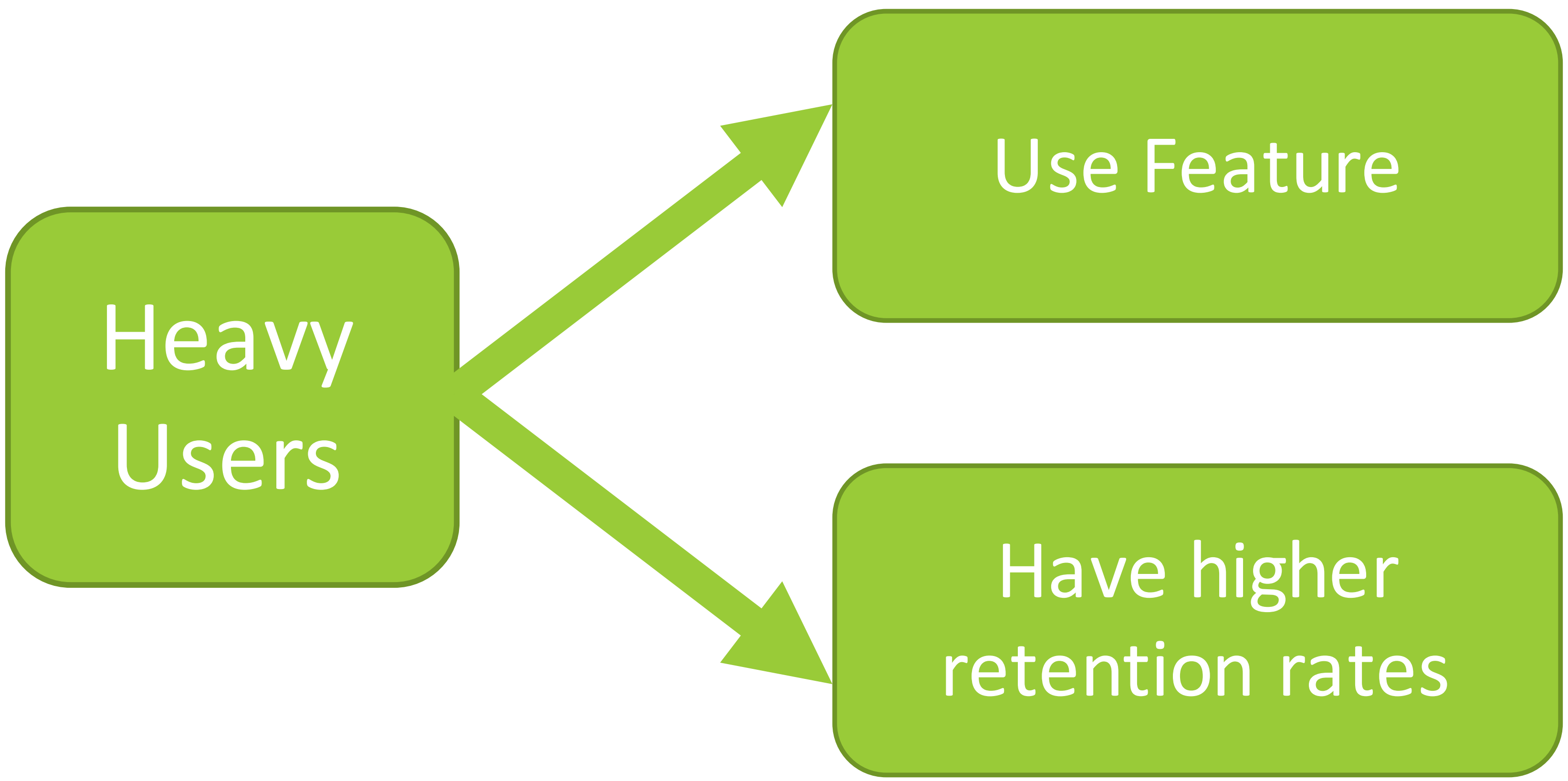
Correlation does not Imply Causation

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



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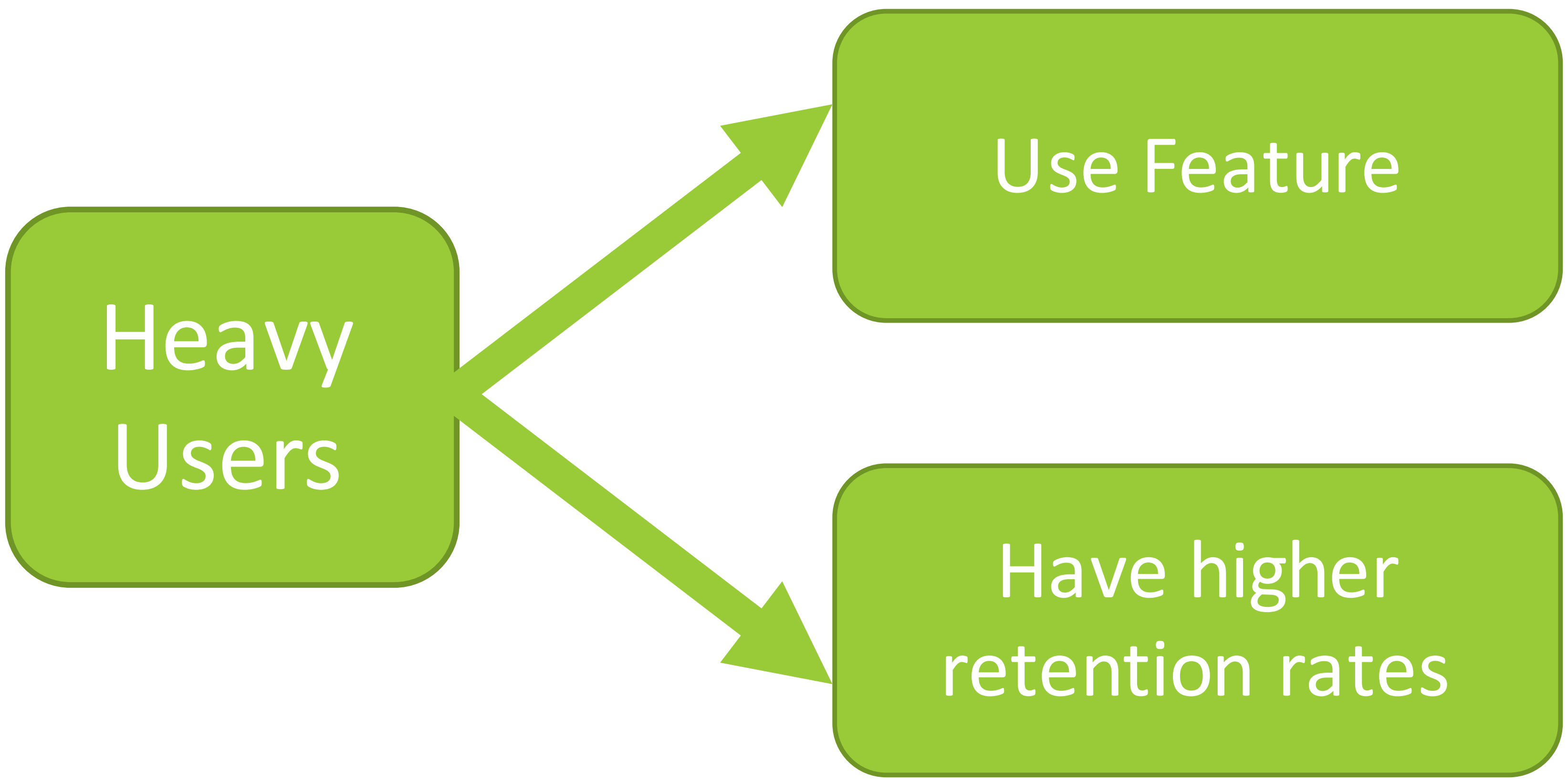
Correlation does not Imply Causation

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



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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)

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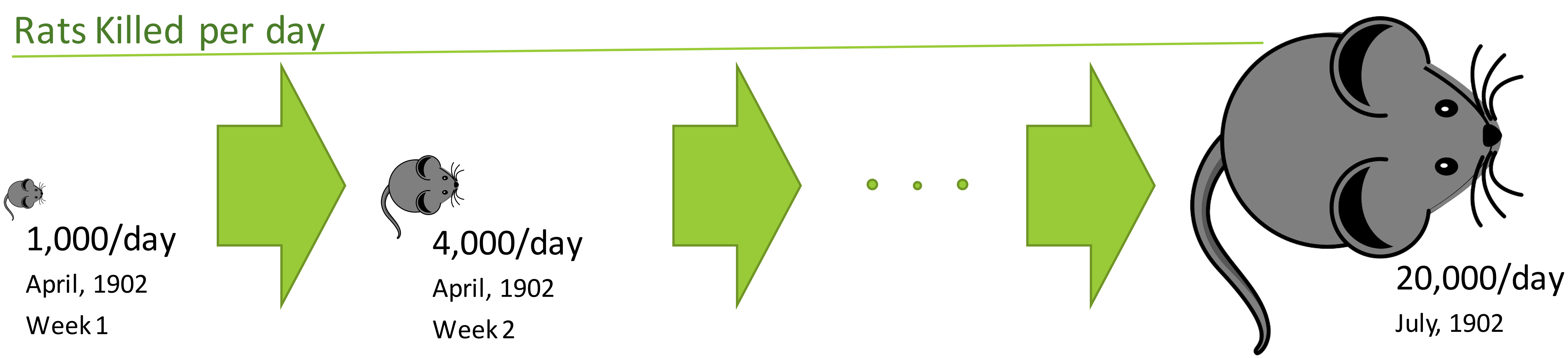
Using the wrong metric

- Hanoi's French Quarter rat problem in 1902



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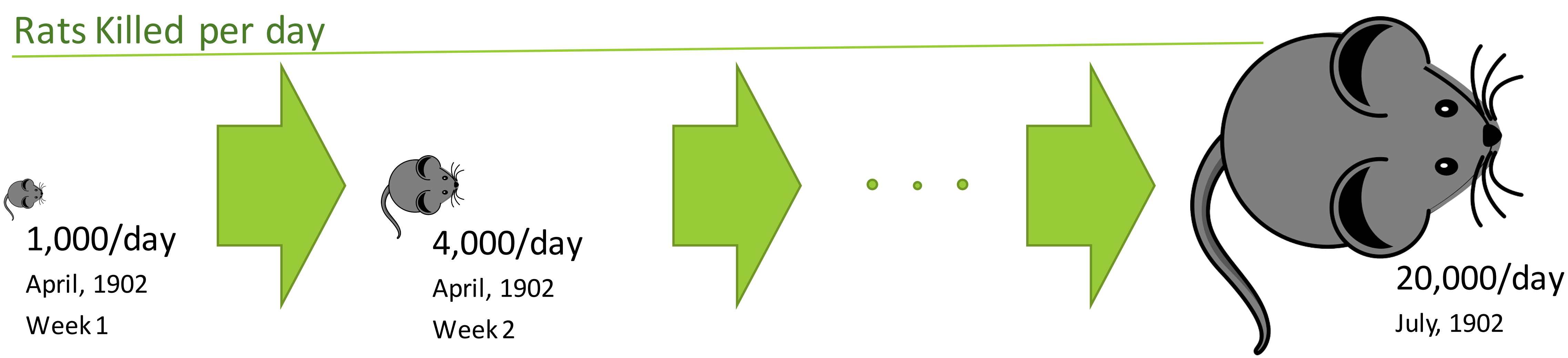

- What you do not measure, does not improve.
- Goodhart's law: "when a measure becomes a target, it ceases to be a good measure"

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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?

```
<a href="https://www.thesitewizard.com/" target="_blank">thesitewizard.com</a>
```

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Making Untested Claims

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

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Making Untested Claims

- Question: What is the effect of SERP load-time on ad-click 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?
- Assumes (bi-directional) linear relationship

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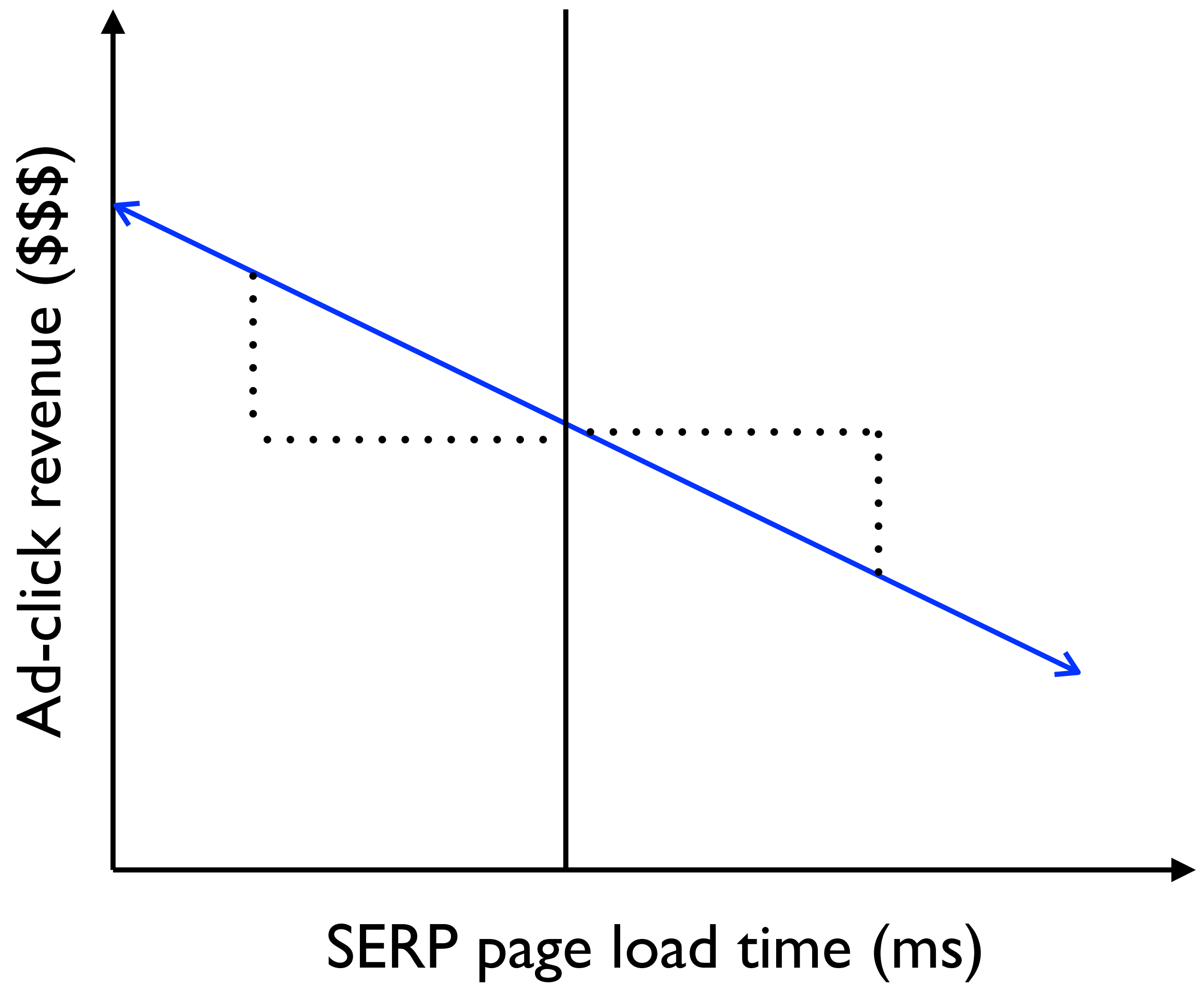
Making Untested Claims



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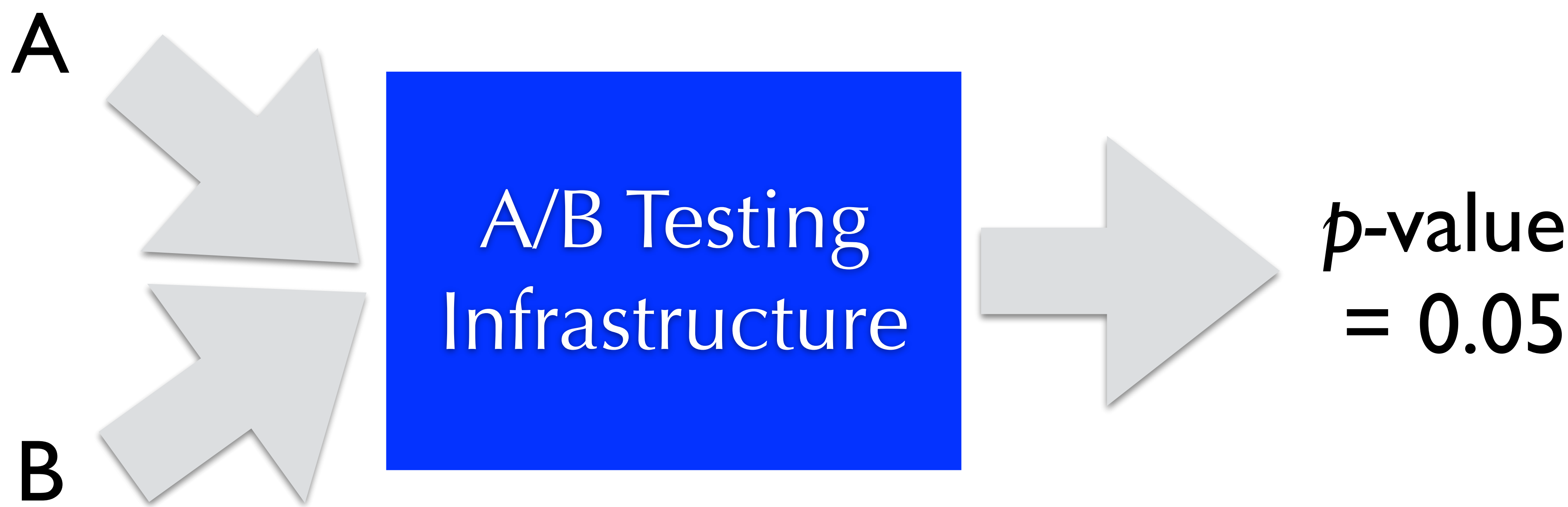
Bugs in the Experimental Infrastructure



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

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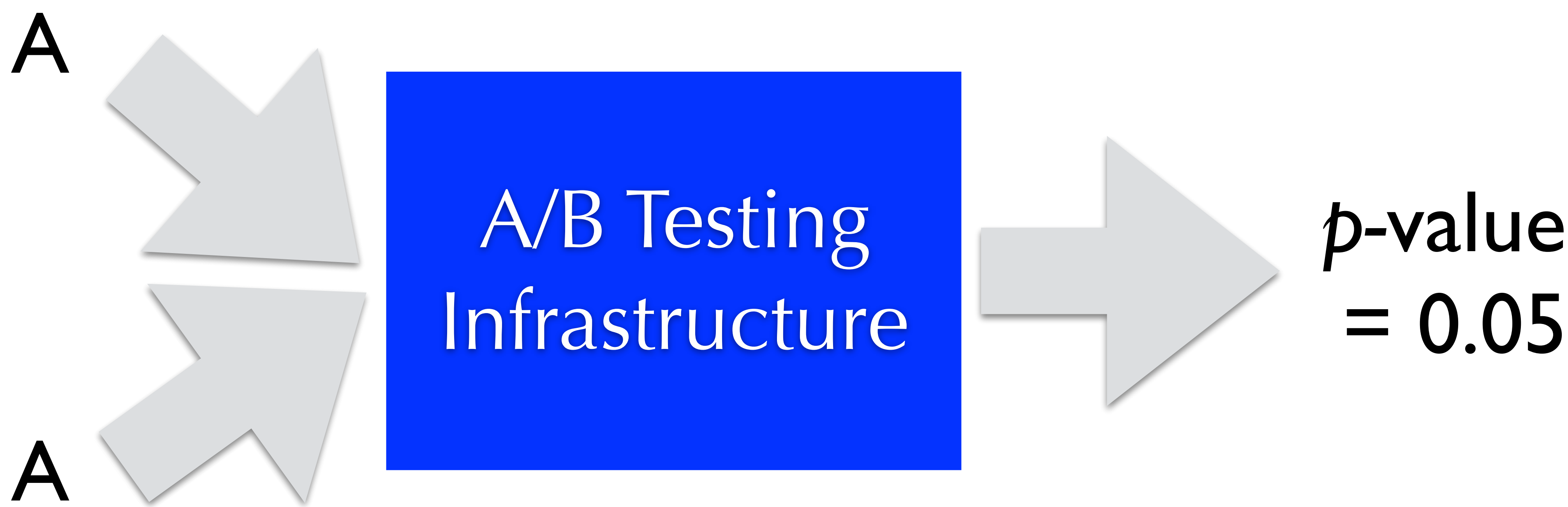
Bugs in the Experimental Infrastructure



- 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?

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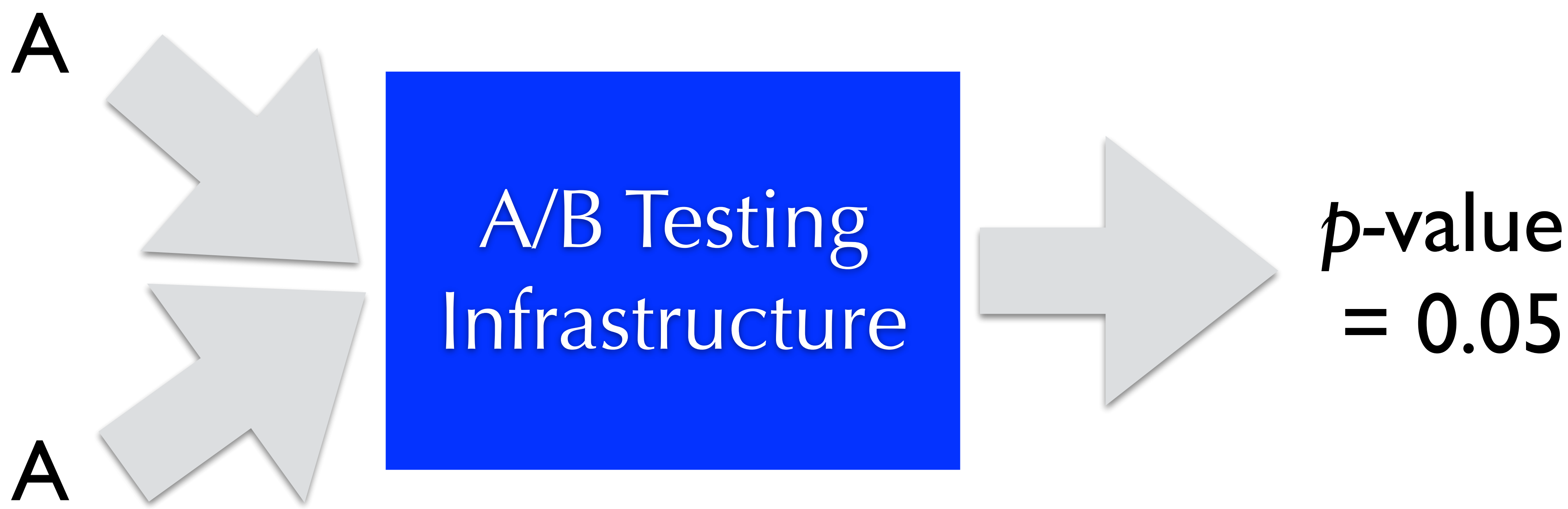
Sound Statistical Methods



- 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?

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Sound Statistical Methods

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

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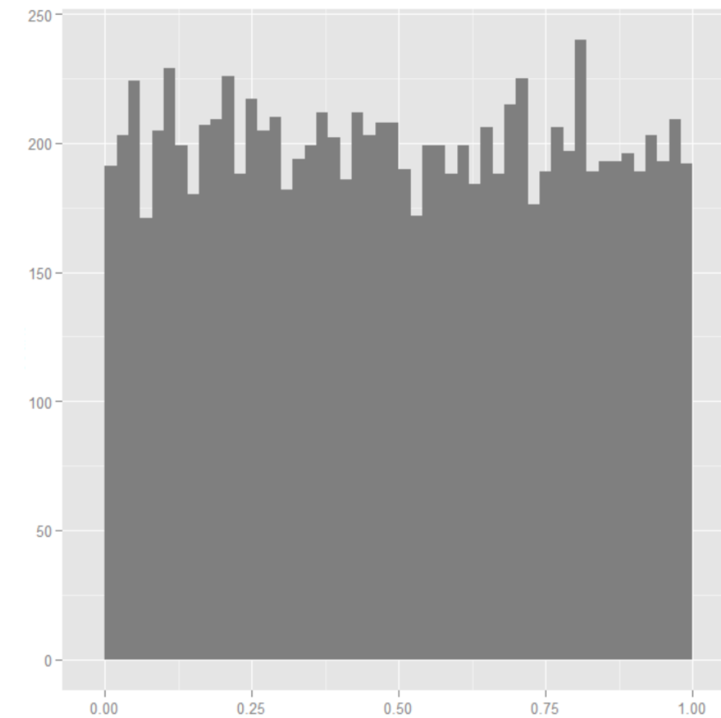
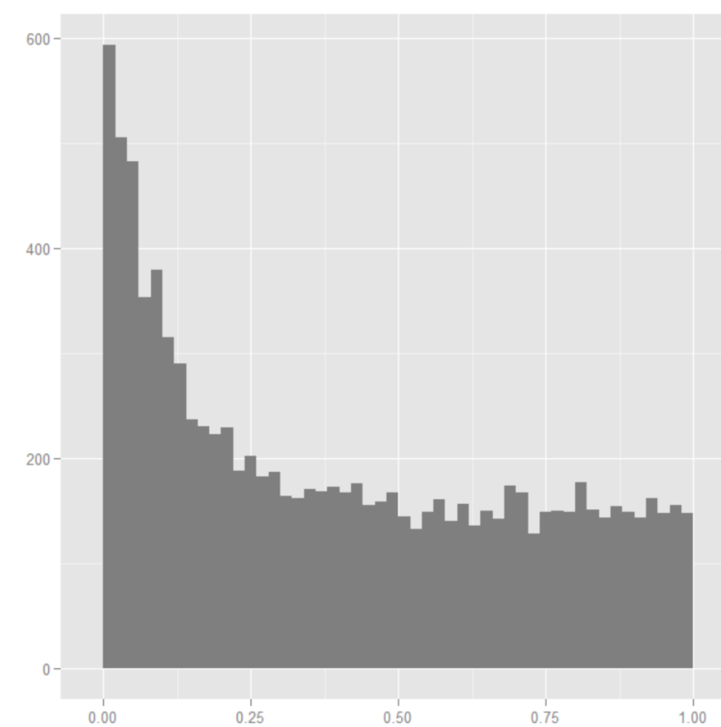
A/A Testing

- 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

Good *p*-values



Bad *p*-values



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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

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Causes of Type I Errors (False Positives)

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

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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

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Cautionary Steps: Starting Small

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

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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)

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Cautionary Steps: Measuring interactions

<table>
<tr><td></td><td></td><td colspan="2">Exp. 2</td></tr>
<tr><td></td><td></td><td>A’</td><td>B’</td></tr>
<tr><td rowspan="2">Exp. 1</td><td>A</td><td rowspan="2">Sig</td><td rowspan="2">No Sig</td></tr>
<tr><td>B</td></tr>
</table>

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Cautionary Steps: Measuring interactions

Exp. 2

Exp. 1

	A’	B’
A	Sig	Sig
B		

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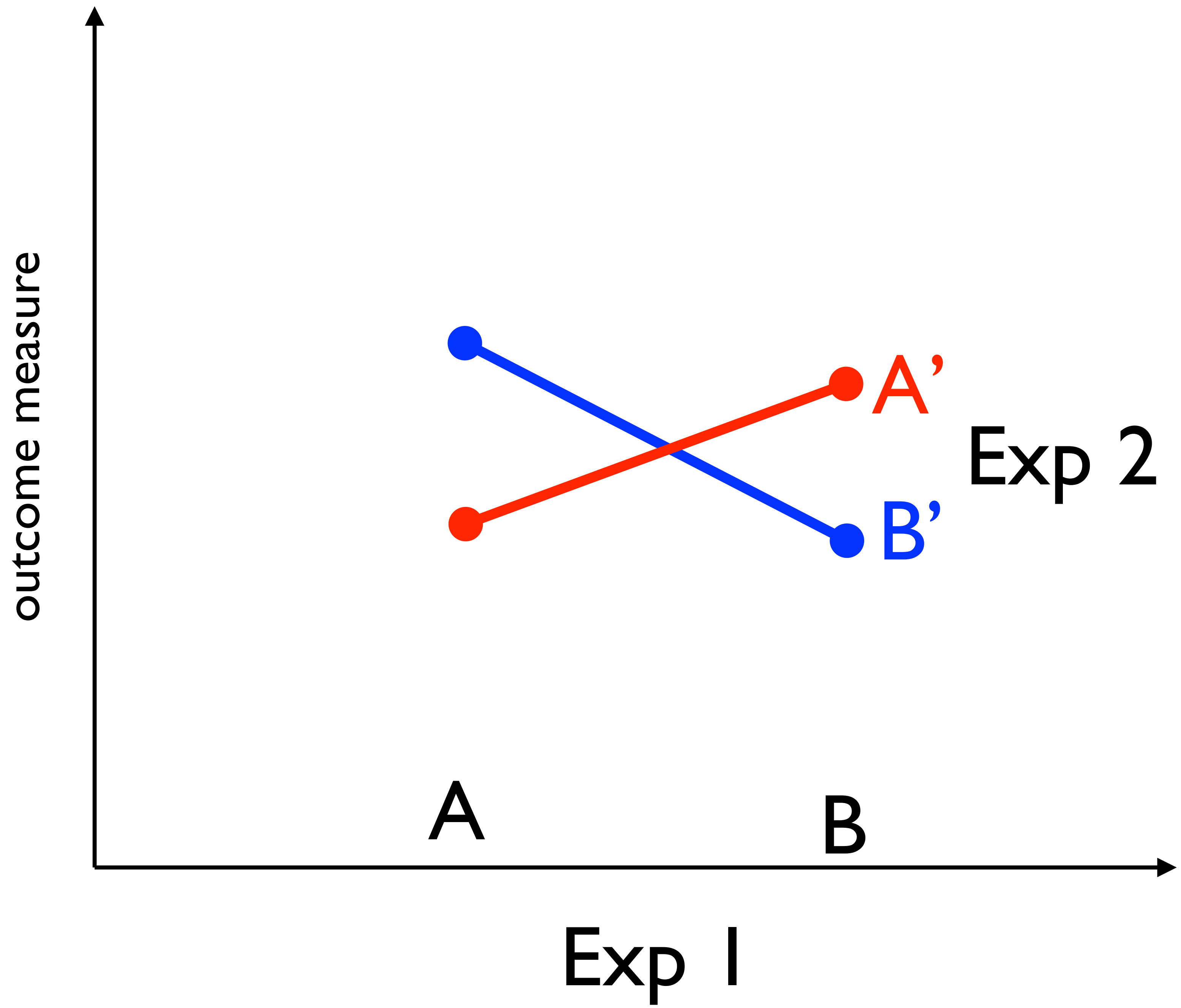
Cautionary Steps: Measuring interactions



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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

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