

Date: Tuesday, May 7, 2019

ANNOUNCEMENTS:

- HW #4 due Friday @ midnight
- Quiz #4 on Thursday morning
 - Will cover the pitfalls & challenges of A/B testing (2 slide decks + jupyter notebook)
 - Multiple Choice
- Final Exam
 - Due Tuesday, May 14th @ 5 p.m.
 - Take home
 - Cumulative
 - Multiple choice
 - Will be up on Thursday
- Thursday: 3:15 p.m. – 5:00 p.m.

Make-up class

1st floor rooms



Example:



TinyCO \rightarrow we use device as our unit

- Design an A/B test on device
- User information gives us an idea of what user has what device, but it can be incorrect 5% of the time.
- TinyCO makes inference @ the user level instead of the device level.

* TinyCO measures

- $\bar{X}_A \rightarrow$ Sample mean for group A
- $\bar{X}_B \rightarrow$ Sample mean for group B
- Effect size: $\hat{\delta} = \bar{X}_A - \bar{X}_B$

\rightarrow We have to account for the error ID rate through the values:

- π_{AB} = # of users thought to be in group A but actually in group B
- π_{BA} = Analogous...

\rightarrow The power calculations depend on π_{AB} & π_{BA} and are found in the paper "The Power of an A/B test under interference".

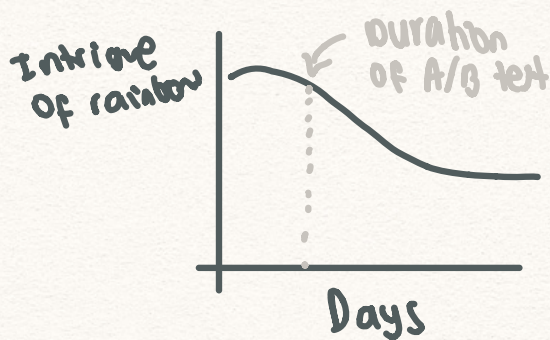
Note: • Companies have a "customer value" metric which is often a function of feature metrics that can be measured.

• The main goal is always to optimize these "customer value" metrics.

Example: Fastclick tests the effect of adding a rainbow to its front page.

- They run the test w/ session duration as the metric.
- At the beginning of the experiment users are really intrigued/excited by the rainbow.

* Mental image:



The intrigue of the rainbow is dictating the measured metric.

Question: How can we gauge the lift effect from new features?

Estimate expected lift based on lift from the past.

- You need to be aware of lift and make sure you run the experiment long enough to see the effect.

One vs Two-tailed tests for effect sizes

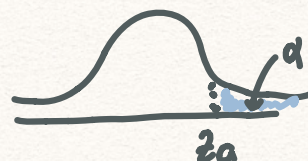
A vs. B

$$\begin{array}{ll} H_0: \mu_A = \mu_B & \text{vs.} \\ \begin{array}{l} H_A: \mu_A \neq \mu_B \\ H_A: \mu_A > \mu_B \\ H_A: \mu_A < \mu_B \end{array} & \left. \begin{array}{l} \} \text{Two-sided} \\ \} \text{One-sided} \\ \} \text{One-sided} \end{array} \right\} \begin{array}{l} \\ \\ \text{(Have more power)} \end{array} \end{array}$$

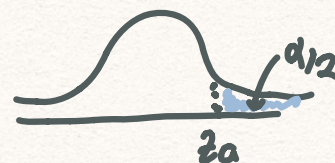
Power: (z-test)

$$z_{\alpha}: P(Z > z_{\alpha}) = \alpha$$

$$\ast \text{ One-sided: } 1 - \beta = P\left(Z > z_{\alpha} - \frac{\delta}{\sigma/\sqrt{n}}\right)$$



$$\ast \text{ Two-sided: } 1 - \beta = P\left(Z > z_{\alpha/2} - \frac{\delta}{\sigma/\sqrt{n}}\right)$$



$z_{\alpha/2} > z_{\alpha}$: This leads to power being greater for one-sided tests for all things ($\alpha, n, \delta, \sigma$) held constant.