Udacity A/B Testing Lesson 1 Notes

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1 Overview of A/B Testing

1.1 Introduction

A/B testing is a general methodology used online when you want to test out a new product or feature.

Two sets of users: Existing product vs. New version

When NOT to use A/B Testing:

- A/B Testing is **not** useful for testing new experiences
  - What is the baseline for comparison?
  - How much time you need for users to adapt to the new experience?
- Time (e.g. apartment rentals → people don't look for apartments that often)
- Cannot tell you if you're missing something

Table 1: When to use A/B Testing Examples

Useful	Not Useful
Movie recommendation site - new ranking algorithm : clear control group and metrics **Change backend - page load time, results users see** : good if computing power available for both **Test layout of initial page** : clear control and metrics	**Online shopping company - Is my site complete?** : could try specific product,but cannot know in general **Add premium service** : could gather information but cannot fully test **Update brand, including main logo** : surprisingly emotional **Website selling cars** : too long and do not have data

Other techniques to use to gather information about users (Qualitative)

- Logs of what users did on the website - Analyze retrospectively to build hypothesis
- User experience research
- Focus groups
- Surveys
- Human evaluation

A/B Testing needs to have a consistent response from your control and experiment group

Goal of A/B Testing is to design an experiment that is going to be robust and give you repeatable results so that one can make a good decision

1.2 Business Example

E.g. Imagine an education company like Udacity called Audacity that focuses on creating finance courses
Goal: To increase student engagement User flow: Customer funnel (largest number of events at the top, where customers go back and forth the funnel)

- Homepage visits
- Exploring the site
- Create account
- Complete a purchase/class

Experiment Initial Hypothesis: Change the Start Now button from *orange* to *pink* will increase how many students explore Audacity's courses

Which metric to use?

- Total number of courses completed (BUT time consuming and not practical as it can take months for students to complete the course)
- Number of clicks (BUT if more total clicks in one version but with lower ration than other version)
- CTR (click-through-rate) $= \frac{Number\ of\ clicks}{Number\ of\ page\ views}$
- CTR (click-through-probability) $= \frac{Unique\ visitors\ who\ click}{Unique\ visitors\ to\ page}$

Use rate when you want to measure the usability of a site and a probability when you want to measure a total impact and disregard double-clicks, reloads, etc.

Updated Hypothesis: Change the Start Now button from *orange* to *pink* will increase the click-through-probability of the button

Repeated measurement of click-through-probability

- visitors = 1000
- unique clicks = 100
- click-through-probability ≈ 10%

  Which results would surprise you if you repeated the measurement?

  - 100
  - 101
  - 110
  - 150 (above what I expected)
  - 900 (above what I expected)

1.3 Hypothesis Testing

p_{cont} and p_{exp}

Null hypothesis H_0: If changing button had no effect, where $p_{exp} - p_{cont} = 0$

Alternative Hypothesis H_A: $p_{exp} - p_{cont} \neq 0$

Steps

- Measure $\hat{p_{cont}}$ and $\hat{p_{exp}}$
- Compute the probability that this difference would have arisen by chance if the null hypothesis were true. P($\hat{p_{exp}} - \hat{p_{cont}} | H_0$)
- Reject H_0 if the above probability is small enough (p < 0.05)

Question: Choosing H_0 and H_A

- Change checkout flow of online shopping site
- Test old flow vs. new flow
- Measure probability of completing checkout

Null hypothesis: The experimental and control groups have the same probability of completing a checkout

Alternative Hypothesis: The experimental and control groups have a different probability of completing a checkout

Then, what change in the click-through probability is substantive/practically significant?

Size your experiment appropriately, such that the statistical significance bar is lower than the practical significance bar

Audacity example: 2 percent change in the click-through probability would be practically significant

1.4 How Many Page Views

- Probability of falsely concluding the difference: α = P(reject null $|H_0$ true)
- Probability of failing to reject H_0 when the H_0 was false: β = P(fail to reject — H_0 false)
- **Small sample**: α is low, β is high (Unlikely to launch a bad experiment, but likely to fail to launch an experiment that actually did have a difference you care about)
- **Larger sample**: α same, β lower (Beta goes down, Power increases)
- Typically consider β at your practical significance boundary
- **Sensitivity**: $1 - \beta$
- In general, you want high sensitivity at the practical significance boundary. People often choose **80 percent**
- If number of samples increase, SE will decrease, so the distribution of results will be narrower, and to keep α the same, the cutoffs for rejecting the H_0 will be closer to 0 (Mean).

1.5 Calculating Number of Page Views

- Built-in library
- Look up answer in a table
- Online calculator (where minimum detectable effect = Practical significance level)
- E.g. How many page views will we need in each group?

- N = 1000
- X = 100
- $d_{min} = 0.02$ (minimum difference we care about)
- $\alpha = 0.05$
- $\beta = 0.02$
- Baseline conversion rate: $\frac{100}{1000} = 10\%$
- Answer: 3623 page views per group

Table 2: How number of page views varies

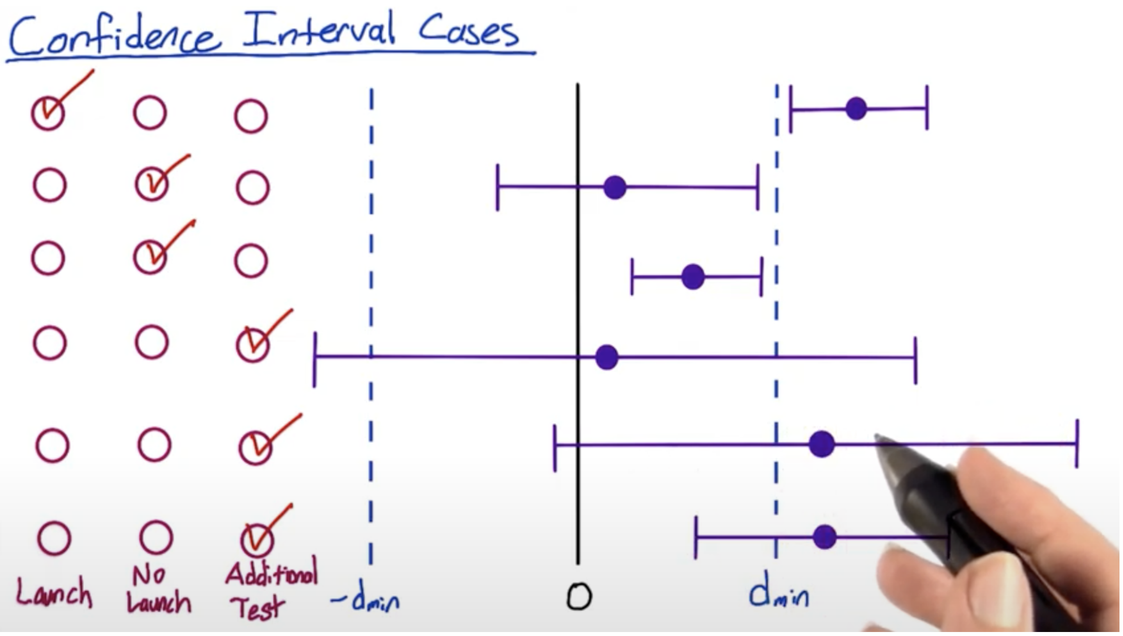
Change	**Increase page views**	**Decrease page views**
Higher click-through-probability in control (but still less than 0.05)	✓	
Increased practical significance level (d_{min})		✓
Increased confidence level ($1-\alpha$)	✓	
Higher sensitivity ($1-\beta$)	✓	

- Standard Error depends on the click-through-probability. $SE = \sqrt{\frac{p(1-p)}{N}}$ As you probability gets closer to 0.5 and further away from the extremes (e.g. 0.1 or 0.9), SE increases.Therefore, need to increase number of page views to get SE to original level.
- d_{min}: larger changes are easier to detect so do not need as many page views.
- Increase CI: Want to be more certain that a change has occurred before rejecting H_0. Want to keep sensitivity the same so need to increase page views.
- Increase sensitivity: Need to collect more page views to narrow the distribution.

1.6 Analyze Results

- $N_{cont} = 10,072$, $N_{exp} = 9886$
- $X_{cont} = 974$, $X_{exp} = 1242$
- $d_{min} = 0.02$
- Confidence Level = 95%
- Pooled Probability = $\hat{p_{pool}} = \frac{974+1242}{10,072+9886} = 0.111$
- Pooled SE = $SE_{pool} = \sqrt{0.111(1-0.111)(\frac{1}{10,072} + \frac{1}{9886})} = 0.00445$
- Estimated Difference = $\hat{d} = \frac{X_{exp}}{N_{exp}} - \frac{X_{cont}}{N_{cont}} = 0.0289$
- Margin of Error = $m = SE_{pool} * 1.96 = 0.0087$ (z-score for CI of 95%)
- Lower Bound =$\hat{d} - m = 0.0202$
- Upper Bound = $\hat{d} + m = 0.0376$
- It is highly probable that click-through-probability changed by at least 2%
- Both statistical and practical significance satisfied: 2% and 5%
- Therefore, launch the new version

1.7 Confidence Interval Cases



- **Second result**: Often called neutral. No statistically significant change from 0 since CI includes 0 and you're also confident that there's not a practically significant change.
- **Third result**: Result is statistically significant. Confident that there was a positive change, but not practically significant. Confident there was a change, but do not care about the magnitude of the change. Therefore, not worth effort to launch the change.
- **Fourth result**: If you ran an experiment and found that it could be causing your number of users to increase by 10% or decrease by 10%. Therefore, not enough power to draw a strong conclusion.
- **Fifth result**: Point estimate is beyond what is practically significant. But CI overlaps at 0, so there might not even be a change at all. Therefore, repeat with greater power.
- **Sixth result**: Possible that change is not practically significant. Therefore, run tests with greater power.

What to do when the last three cases come up but you do not have time to run a new experiment?

- Communicate to decision-makers when they're going to have to make a judgement, and take a risk, because the data is uncertain
- Use other factors: Strategic business issues

1.8 Statistics Review

- **Binomial Distribution**
  (Successes/Failures) e.g. (click = success, no click = failure)
  - biased user who has $p = \frac{3}{4}$ of clicking a page
  - success = click, failure = no click
  - As $N \to \infty$, binomial $\to$ normal
  - $mean = p$, $stddev = \sqrt{\frac{p(1-p)}{N}}$
  - Assume p not known

- * e.g. N = 20, clicks = 16, Estimate the bias $\hat{p} = \frac{4}{5}$
- When to use binomial
  - * 2 types of outcomes
  - * independent events
  - * identical distribution: p same for all

- **Confidence Intervals**
  For a 95% confidence interval, if we theoretically repeated the experiment over and over again, we would expect the interval we construct around the sample mean to cover the true value in the population 95% of the time
  - $\hat{p} = \frac{X}{N}$ where X = number of users clicked, N = number of users
  - e.g. $\hat{p} = 0.1$
  - *To use normal distribution if* $N\hat{p} > 5$ *and* $N(1-\hat{p}) > 5$
  - **Standard Error SE** = $\sqrt{\frac{p(1-p)}{N}}$
  - **Margin of Error m** = $zscore * SE = z * \sqrt{\frac{\hat{p}(1-\hat{p})}{N}}$
    The amount of random variation we expect in our sample is a proportion of both successes and the size of the sample. When the success probability is further from 0.5, then SE would be smaller, which means CI will be smaller.
    Similarly, if N is larger, the SE and CI will be smaller. For 95% CI, z-score will be 1.96 for two-tailed CI.
    m = 0.019 margin = 0.081 to 0.119

- **Hypothesis Testing**
  - Null hypothesis: There is no difference in click-through-probability between our control and experiment
  - Alternative hypothesis: Are we interested in the difference, or just higher or lower?

- **Pooled Standard Error**
  - Number of users who click in each group: X_cont, X_exp
  - Total number of users in each group: N_cont,
  - First, calculate pooled probability of a click (total probability of a click across groups)
    $p_{\hat{pool}} = \frac{X_{cont}+X_{exp}}{N_{cont}+N_{exp}}$
  - Then, calculate pooled standard error
    $SE_{pool} = \sqrt{p_{\hat{pool}} * (1 - p_{\hat{pool}}) * (\frac{1}{N_{cont}} + \frac{1}{N_{exp}})}$
    Difference $\hat{d} = \frac{X_{exp}}{N_{exp}} - \frac{p_{cont}}{N_{cont}} = p_{exp} \hat{-} p_{\hat{cont}}$
  - Under H_0 :, true difference $d = 0$, $\hat{d} \sim N(0, SE_{pool})$
  - If $\hat{d} > 1.96 * SE_{pool}$ or $\hat{d} < -1.96 * SE_{pool}$, reject H_0

- **Size vs. Power Trade-Off**
  - Statistical power: e.g. How many page views needed in order to get a statistically significant result
  - **Power has an inverse trade-off with size**: The smaller the change that you want to detect or the increased confidence you want to have in the result, means larger experiment required, so more page views in control and experiment