# Project 1: Using Simulations To Test Hypotheses

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When companies want to make improvements to their website or other customer interface, they need to be careful that these improvements result in a better customer experience. A common way to test which of two versions of their website is better is with A/B testing. A/B testing compares two versions of the same digital content to determine which performs better on a set of metrics.

In Part One of the course project, you will calculate the results for an A/B test conducted by a software company that wants to determine which of two web page layouts leads to a higher click rate. In this case, click rate is a metric that measures the proportion of visitors who click on a link to a featured product. Currently, the software company uses layout A, but if layout B has a higher click rate, they will switch to layout B.

To perform the A/B test, the software company runs the following experiment: Layout A is presented to a random set of 100 website visitors, and layout B is presented to a different random set of 100 visitors. The results indicate that 62 of the 100 visitors who were shown layout A clicked on the featured product, whereas 74 of the 100 visitors who were shown layout B clicked on the featured product. Now, you need to evaluate the uncertainty around this finding to determine whether this result seems real, or whether it is due to random chance.

### Step 1

Write the null and alternative hypotheses you are evaluating for the A/B test.

 $H_0$ : There is no difference in the click rates generated by Layout A as compared with Layout B.

 $H_a$ : The click rates generated by Layout B are higher than those generated by Layout A.

## Step 2

What is the observed sample statistic from the company's A/B test?

```
CR(LayoutA) = 62/100 = 0.62 CR(LayoutB) = 74/100 = 0.74
sample_statistic = CR(LayoutB) - CR(LayoutA) = 0.74 - 0.62 = 0.12
```

#### Step 3

What are the implications of a Type I error (false positive) and a Type II error (false negative) in this context?

If we incorrectly reject  $H_0$  and accept  $H_a$ , then we would incur a Type I error. The implication is that we believe Layout B will generate a higher click rate than Layout A when, in fact, the difference in click rates between the two layouts is not statistically significant.

If we incorrectly accept  $H_0$  and reject  $H_a$ , then we would incur a Type II error. The implication is that we believe the difference in click rates between Layout A and Layout B is not statistically significant when, in fact, the difference in click rates between the two layouts is statistically significant.

### Step 4

Complete the following starter code to construct the null distribution of the sample statistic (click rate of layout B – click rate of layout A). Complete the five lines that have the comment # COMPLETE after them.

```
# eCornell Hex Codes:
crimson = '#b31b1b'
                      # crimson
lightGray = '#cecece' # lightGray
darkGray = '#606366' # darkGray
skyBlue = '#92b2c4' # skyblue
gold = '#fbb040'
                     # gold
ecBlack = '#393f47'
                    # ecBlack
# Simulate null distribution of statistic
# Both layouts A and B have same chance of success: (74+62)/(100+100) = 68\%
set.seed(1)
outcome = c("Clicked", "Did not Click")
nsim = 100000
store_p_diff = rep(0, nsim)
p_new = 62/100 # Observed click rate of Layout A
p_old = 74/100 # Observed click rate of Layout B
p_{all} = (62+74)/(100+100) # Combined click rate under the null hypothesis = 68\%
for (i in 1:nsim){
result_new = sample(outcome, 100, replace = TRUE, prob = c(p_all, 1-p_all))
p_new_sim = mean(result_new == "Clicked")
result_old = sample(outcome, 100, replace = TRUE, prob = c(p_all, 1-p_all))
p_old_sim = mean(result_old == "Clicked")
p_diff = p_new_sim - p_old_sim
store_p_diff[i] = p_diff
```

#### Step 5

Calculate the mean and standard deviation of the null distribution of the sample statistic you created in Question 4.

```
mean = mean(store_p_diff)
std_dev = sd(store_p_diff)
```

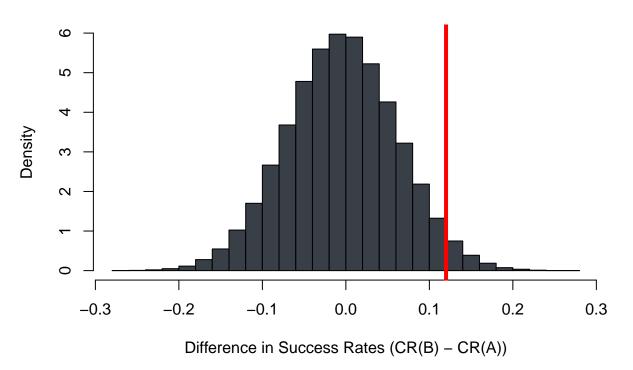
## Step 6

Draw a histogram of the null distribution of the sample statistic. Plot the observed statistic over the histogram.

```
hist(store_p_diff, breaks = 40, freq = FALSE, col = ecBlack,
    main = 'Histogram of Sample Differences (CR(B) - CR(A))',
    xlab = 'Difference in Success Rates (CR(B) - CR(A))')

abline(v = 0.12, lwd = 4, col = "red")
```

## **Histogram of Sample Differences (CR(B) – CR(A))**



Step 7

Calculate the p-value of the observed statistic. Interpret this p-value in the context of this problem. Based on the usual accepted cut-off value of 0.05, would you select the null hypothesis, or reject it in favor of the alternative hypothesis? Briefly explain your decision.

```
# calculate p-value
mean(store_p_diff > 0.12) # = 0.03
```

#### ## [1] 0.02912

Since the p-value < 0.05, we would reject the null hypothesis,  $H_0$ . We conclude this because, if the null hypothesis were true (both Layout A and Layout B had the same 68% click rate in population), there would be only a 3% chance that the difference in click rates is 0.12 or higher. So it does look like there is strong evidence in favor of the alternative hypothesis,  $H_a$ .

## Step 8

Suppose the company decides that they would like to choose layout B if layout B is at least 8% better than layout A. What are the chances of obtaining a false positive with this decision rule?

Looking at the power curve, for a signal value of 0.08, the corresponding power is approximately 0.3. Therefore, there is a 30% chance of obtaining a false positive.

## Step 9

Suppose you want to control the false positive rate at 5%. What cut-off value should you use?

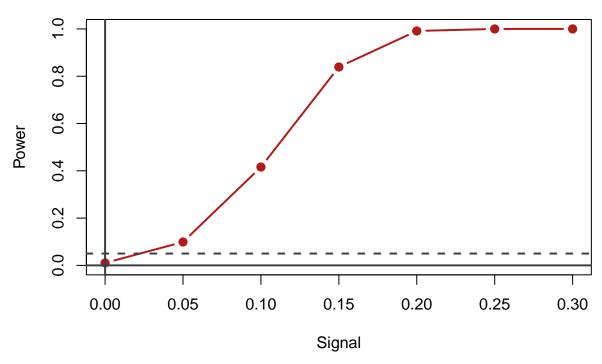
Looking at the power curve, there is a dotted horizontal line plotted for power = 0.05. The corresponding signal is 0.025 or 2.5%, which is our cut-off value.

### Step 10

The following code chunk draws a power curve for these data. Run the code to create the power curve. Then, use the power curve to determine how often you would be able to detect that layout B is better than layout A under the following conditions: - you choose 11% as the cut-off value, and - layout B is 10% better than layout A.

```
# R function to calculate power for a desired signal level:
calc_power <- function(delta){</pre>
set.seed(1)
outcome = c("Clicked", "Did not Click")
nsim = 100000
store_p_diff = rep(0, nsim)
p_{new} = 74/100
p old = 62/100
p_all = (74+62)/(100+100)
for (i in 1:nsim){
result new = sample(outcome, 100, replace = TRUE, prob = c(p all+delta, 1-p all-delta))
p_new_sim = mean(result_new == "Clicked")
result_old = sample(outcome, 1000, replace = TRUE, prob = c(p_all, 1-p_all))
p_old_sim = mean(result_old == "Clicked")
p_diff = p_new_sim - p_old_sim
store_p_diff[i] = p_diff
return(mean(store_p_diff > 0.11))
# Use this function to calculate power for signal levels 5%, 10%, 15%, ...
delta_seq = seq(0, 0.3, by=0.05)
power_seq = rep(0, length(delta_seq))
for (i in 1:length(delta_seq)){
  delta = delta_seq[i]
  power_seq[i] = calc_power(delta = delta)
  print(paste('signal = ', delta, '; power = ', round(power_seq[i], 4)))
## [1] "signal = 0; power = 0.0103"
## [1] "signal = 0.05; power = 0.099"
## [1] "signal = 0.1; power = 0.4158"
## [1] "signal = 0.15; power = 0.839"
## [1] "signal = 0.2; power = 0.9915"
## [1] "signal = 0.25; power = 1"
## [1] "signal = 0.3; power = 1"
# Plot the power curve:
plot(delta_seq, power_seq, type = 'b', pch = 19, lwd = 2, col = crimson,
     xlab = 'Signal', ylab = 'Power', main = 'Power Curve',
     ylim = c(0,1), xlim = c(0, 0.3)
abline(h = 0.05, col = ecBlack, lwd = 2, lty = 2)
abline(h = 0, col = ecBlack, lwd = 2, lty = 1)
```

## **Power Curve**



We choose 11% as the cut-off value:

There is a 50% chance of finding that layout B is better than layout A with a cut-off rule that controls the chance of a false positive at 5%.

Layout B is 10% better than layout A.

With a signal = 0.1, there is a 42% of finding that Layout B is 10% better than layout A.

This is the end of Part One of the course project.

Don't forget to submit your work!