# A/B testing for Marketing Strategies and Data- driven Decisions

## Conduct A/B testing to evaluate the impact of different marketing strategies and make data-driven decisions.

* 1. Design and implement A/B tests for marketing campaigns using randomized assignment.
  2. Collect relevant data and perform statistical analysis to compare the performance of different strategies.
  3. Calculate key metrics such as conversion rates, clickthrough rates, or revenue.
  4. Interpret the results and provide recommendations for optimizing marketing campaigns based on the findings.

[This dataset](https://www.kaggle.com/datasets/putdejudomthai/ecommerce-ab-testing-2022-dataset1/) contains A/B test results for an e-commerce website. A subset of users were exposed to a new landing

page, and the current goal is to asses the effect of this new page on the conversion rate. library(tidyverse)

library(infer) library(scales) library(forcats)

ab\_data <- read\_csv("F://ab\_data.csv",show\_col\_types = FALSE) sample\_n(ab\_data, 5)

ab\_data <- ab\_data %>%

mutate(landing\_page = fct\_rev(landing\_page), # set order to (old\_page, new\_page) converted = factor(converted)) # categorical required in infer proportion tests

ab\_data %>% group\_by(group) %>% tally()

1. control 147202
2. treatment 147278

Some of the users appear more than once: ab\_data %>%

group\_by(user\_id) %>%

add\_tally(name = "num\_of\_appearances") %>% arrange(desc(num\_of\_appearances), user\_id) %>%

head()

The conversion rate is slightly higher in the control group (0.1204 vs 0.1189), indicating that the new landing page performed poorly.

conversion\_rate\_by\_group <- ab\_data %>% group\_by(group) %>%

summarise(conversion\_rate = mean(converted == "1")) conversion\_rate\_by\_group

conversion\_rate\_by\_group %>%

ggplot(aes(x = group, y = conversion\_rate, fill = group)) + geom\_col(width = 0.5) +

geom\_label(aes(label = label\_number()(conversion\_rate)), family = "serif") + labs(x = "Group", y = "Conversion Rate", title = "Conversion Rate by Group") + guides(fill = "none")

Some of the users in the control group were exposed to the new page, and some of the users in the treatment group were exposed to the old page:

ab\_data %>%

group\_by(group, landing\_page) %>% summarise(count = n()) %>%

ggplot(aes(x = group, y = count, fill = landing\_page)) + geom\_col(position = position\_dodge(width=1)) +

geom\_label(aes(label = comma(count)), position = position\_dodge(width=1), size=3.5, family = "serif") + labs(title = "Count of Users by Group & Page", x = "Group") +

scale\_y\_continuous(name = "Count", labels = comma)

`summarise()` has grouped output by 'group'. You can override using the

`.groups` argument.

The new page did better in the control group. The old page did better in the treatment group: ab\_data %>%

group\_by(group, landing\_page) %>% summarise(conversion\_rate = mean(converted == "1")) %>% ggplot(aes(x = group, y = conversion\_rate, fill = landing\_page)) + geom\_col(position = position\_dodge(width=)) +

geom\_label(aes(label = label\_number()(conversion\_rate)), family = "serif", position = position\_dodge(width = 1)) + labs(x = "Group", y = "Conversion Rate", title = "Conversion Rate by Group & Page")

Inference

1. 95% Confidence Interval

Let's construct a 95% confidence interval for the difference in conversion rates between the test group and the control group. The observed value from our data is -0.001481, which is quite small

diff\_in\_proportions <- ab\_data %>% specify(converted ~ group, success = "1") %>%

calculate("diff in props", order = c("treatment", "control")) diff\_in\_proportions

A tibble: 1 × 1 stat

<dbl>

1 -0.00148

We'll proceed as follows:

estimate the sampling distribution of the difference in proportions (conversion rates) using bootstrap resampling use the estimated standard error from the bootstrap distribution to create the confidence interval.

bootstrap\_dist <- ab\_data %>% specify(converted ~ group, success = "1") %>% generate(reps = 500, type = "bootstrap") %>%

calculate(stat = "diff in props", order = c("treatment", "control"))

visualise(bootstrap\_dist) +

labs(x = "Difference in Conversion Rates", y = "Count")

ci <- get\_ci(bootstrap\_dist, level = 0.95, type = "se", point\_estimate = diff\_in\_proportions) ci

lower\_ci upper\_ci

<dbl> <dbl>

1 -0.00376 0.000796

We can say with 95% certainty that the difference in conversion rates is in the range (-0.003795, 0.000832).

Zero is inside this confidence interval, implying that the difference in conversion rates is quite possibly not statistically significant (the difference can be zero i.e. no difference).

1. Hypothesis Testing

*Is the conversion rate for the treatment group significantly different from that of the control group?*

1. Simulation

This involves approximating the sampling distribution of the difference in conversion rates under the assumption that the null hypothesis is true. null\_dist <- ab\_data %>%

specify(converted ~ group, success = "1") %>% hypothesize(null = "independence") %>%

generate(reps = 500, type = "permute") %>% # shuffling calculate(stat = "diff in props", order = c("treatment", "control")) visualise(null\_dist) +

shade\_p\_value(obs\_stat = diff\_in\_proportions, direction = "both") + labs(x = "Difference in Conversion Rates", y = "Count")

get\_p\_value(null\_dist, obs\_stat = diff\_in\_proportions, direction = "both") p\_value

<dbl> 1 0.212

We fail to reject the null hypothesis at level of significance 0.05 since the *p-value* 0.18 > 0.05. We do not have sufficient evidence that the difference in conversion rates is statistically significant.

1. Theoretical

[prop\_test](https://infer.tidymodels.org/reference/prop_test.html) can be used to test the null hypothesis that the proportions in several groups are similar (difference = 0). It performs [Pearson's Chi-squared test,](https://en.wikipedia.org/wiki/Pearson%27s_chi-squared_test) which requires that:

sample data is drawn at random (depends on how this dataset was collected - we'll assume it was random) the sample is sufficiently large (this condition is met)

observations are independent of each other (some users appear more than once - not fully met) prop\_test(ab\_data, converted ~ group, order = c("control", "treatment"),

conf\_level = 0.95, success = "1")

statistic chisq\_df p\_value alternative lower\_ci upper\_ci

<dbl> <dbl> <dbl> <chr> <dbl> <dbl>

1 1.52 1 0.218 two.sided -0.000870 0.00383

Once again, the p-value 0.2177 > 0.05 and we fail to reject the null hypothesis.

### Output:

**Interpretation and Implications:** The new landing page did not boost the conversion rate. The difference in conversion rates between the new page and the old one is not statistically significant.

We need to investigate what aspects of the new landing page failed to motivate purchases, and make the necessary improvements.