Ad A/B Testing

Final Report

Problem Statement

A/B testing is, at its most basic, a way to compare two versions of something to figure out which performs better. This method of testing has been around for a long time and is an intuitive way to compare similar things. Its no wonder that A/B testing is still an important testing method used by businesses today to look at any number of metrics (eg. customer engagement, web traffic, revenue) and see which version increases performance.

AdSmart is looking to increase customer engagement with their questionnaire. They have recorded the data on users that have seen a dummy ad and users that have seen the new ad. Which version of their ad performs better?

Datasets

- AdSmartABdata – A dataset from a company running an a/b test on a new advertisement to test customer engagement with their questionnaire.
    - Half of the users are given a dummy ad and the other half are given the new ad.

Data Wrangling

The data was mostly clean already. There were no null values, and a couple of columns needed to be adjusted. The date and hour column were converted to datetime and merged into 1 column. The yes and no column merged into a success column and no response column was added

Success tracks if the user clicked on yes on the questionnaire at the end of the ad. No response tracks if the user did not respond to the questionnaire. Each combination of these metrics shows every possible combination of user engagement.

- if success is 0 and no_response is 0 - user clicked on no after the ad
- if success is 1 and no_response is 0 - user clicked on yes after the ad
- if success is 0 and no_response is 1 - user neither clicked on yes or no
- if success is 1 and no_response is 1 - not possible in our implementation.

EDA

The first thing I did when exploring the data was to check the sample size of the control and exposed group. After I confirmed that each group had roughly 4000 users, I then moved on to explore the breakdown of each of the different metrics to measure user engagement. Seen in Figure 1

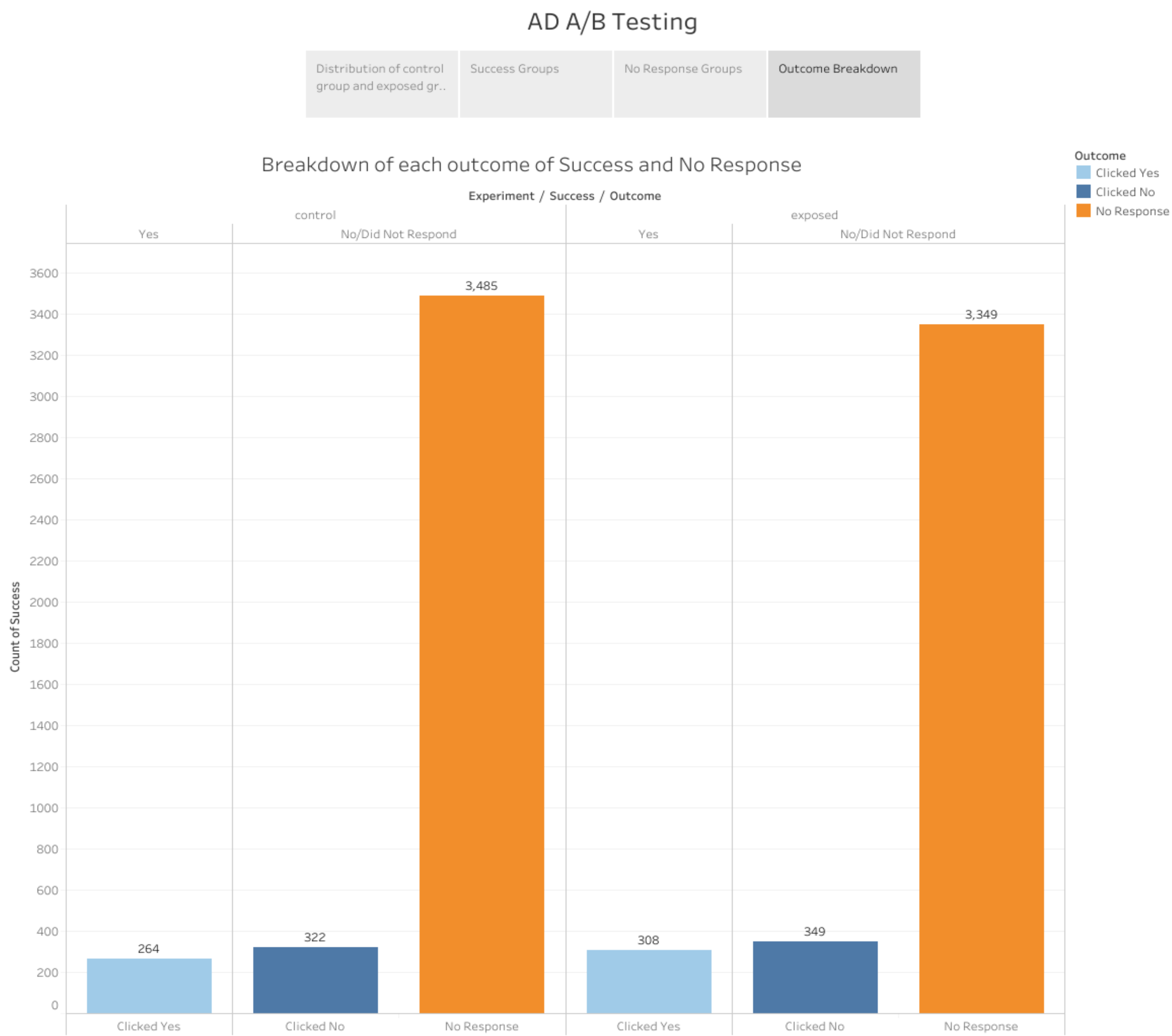

Figure 1: Breakdown of user outcomes in control and exposed group

The data has an overwhelming majority of no responses. Most people that saw either ad declined to answer the questionnaire at the end. However, I chose to keep the no response column as I also wanted to measure the customer disengagement rate between groups.

I can now answer three different questions about the data in the modeling section. How does our new ad perform when looking at the yes responses vs no/no response? How does our ad perform when looking at just the yes responses vs no responses? And how does our ad perform when looking at those that responded vs no response?

Modeling

For my model, I used a Z test as the sample size of my data was large enough that the distribution was roughly normal

Z Test - yes vs no/noresponse

Null hypothesis: There is no significant difference between the ad success rate of both groups

Alt hypothesis: There is significant difference between the ad success of both groups

p value: 0.035

Since the p value is less than 0.05, then we reject the null hypothesis. There is a significant difference in ad success between the control group and the exposed group.

The exposed group were more likely to click yes after viewing the new ad. The ad success rate of the control group was found to be 6.48% and the exposed group to be 7.69%

Z Test – yes vs no

Null hypothesis: There is no significant difference between the questionnaire engagement rate of both groups

Alt hypothesis: There is significant difference between the questionnaire engagement rate of both groups

p value: 0.052

Since the p value is greater than 0.05, then we fail to reject the null hypothesis. There is no significant difference in questionnaire engagement between the control group and the exposed group.

That means that when filtering out the no response answers. The proportion of users that clicked on yes or no is about the same in both groups.

Z test - No Response vs Response

Null hypothesis: There is no significant difference between ad disengagement rate between groups

Alt hypothesis: There is significant difference between ad disengagement rate between groups

value: 0.012

Since the p value is less than 0.05, then we reject the null hypothesis. There is a significant difference in questionnaire disengagement rate in the control group and the exposed group.

That means that the exposed group were less likely to click away from the ad and answer yes or no at the end of the ad. The new ad has a better response rate from users and could also mean that it is better at converting customers into a response, either yes or no.

Outcome Table

Test	P Value	Results
Yes vs no/no response	0.035006	Reject the null hypothesis. There is a significant difference in ad success between the control group and the exposed group
Yes vs no	0.518486	Fail to reject the null hypothesis. There is no significant difference in questionnaire engagement between the control group and the exposed group.
no response vs response	0.012495	Reject the null hypothesis. There is a significant difference in questionnaire disengagement between the control group and the exposed group.

Insights & Recommendations

Insights

- When looking at the different statistical models, we ran the model on different metrics of 'success'
- The test for yes vs no/response shows that the differences between control and exposed group was significant. The new ad had an improved impact on customers engaging in the questionnaire
- The data shows the ad success rate of the control group to be 6.48% and the exposed group to be 7.69%
- The test for only Yes vs No responses shows that the differences were not significant.
- The test for no response rate shows that there is a significant difference between the control and exposed group. The exposed group has a lower rate of no response compared to the control group.
- The data shows the ad no response rate of the control group to be 85.61% and the exposed group to be 83.60%
- That would mean that the new ad not only performs better on all customers, but is also better at converting customers that normally would not respond

Recommendations

- First recommendation – The data suggests that when looking at yes responses vs no/no response and no response rate the business should use the new ad as it has shown to increase ad success and higher customer engagement
- Second recommendation – When looking at the data of yes responses vs no responses, the data suggests that the business should keep with the old ad, if it is only concerned about the customers that stayed to the end of the ad. However, I would personally steer away from the

old ad shown in the other two tests that more people respond to the new ad, and less people click away while in the middle of the ad

- Third recommendation – When looking at the data of no response vs response data, the data suggests that the business use the new ad as on average the no response rate of the control group to be 85.61% and the exposed group to be 83.60%. The new ad can reach a wider audience with the higher engagement rate

Further Research

This experiment looked at how many people answered AdSmart's questionnaire. Further A/B testing and experimentation could be done to see if the new ad translated to more revenue for the company.

Further research could also be done on expanding the data that is gathered on users, such as gender or locational data. The new ad could be further refined to target which platform users accessed the Ad from. All of these factors would help AdSmart target specific audiences more efficiently.