Udacity Project 7: Design an A/B Test

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Experiment Design

Metric Choice

Invariant Metrics:

- Number of cookies - since the experience of a user does not change before they view the course overview page, we expect around the same number of cookies to view it. The change is not revealed until after they click the "start free trial" button". A change in this metric could indicate something fishy with our experiment.
- Number of clicks - similarly we expect a relatively similar number of unique cookies to click the "start free trial" button, since this happens before the screener is revealed
- Click through probability - given that we expect the number of cookies and the number of clicks to remain consistent, logically we would also expect the click through probability (clicks / cookies) to also remain stable.

Evaluation Metrics:

- Gross conversion - since the change implemented intends to screen out individuals who may not be able to commit enough time to complete the course, we are looking to test if the number of user-ids that complete checkout and enroll in the free trial divided by the number of unique cookies is lower. This would mean people were deterred from even beginning the free trial and the screening worked well. In order to launch we will need to see a significantly lower gross conversion rate.
- Net conversion - screening out individuals less prone to committing the necessary time could also mean that the number of individuals who enroll after 14 days divided by the number of unique cookies that clicked the start free trial could change. In this experiment, it will be important that the net conversion does not decrease. If it did, this could lead to less paying customers in the long term. In order to launch we will need to confirm that there is not a significant decrease in net conversion.

Unused Metrics:

- User ID - The main reason it is not used as an invariant metric is that we expect the number of user IDs that enroll in the free trial to change when the screening is done. Although it could technically be used as an evaluation metric, but in the case of this experiment using a rate or probability metric as opposed to a sum or count is a better option. For example, we could see a significant increase in users signing up for the free trial, but could only be due to the fact that there was more traffic to the site (perhaps due to some seasonal effect) and more people were clicking the "start free trial" button. This would lead to a significant difference in the number of user ID’s but not in gross conversion.

- Retention - since the screening intends to deter individuals who may not be as willing to commit time to the course (and therefore are more willing to give up in the first 14 days), one would hope that screening out these individuals also increases the proportion of people who enroll in the free trial and actually end up paying after staying on for more than 14 days. However, this metric requires far more page views then both of the conversion metrics, and would cause the experiment to take far too long. Therefore, it is being excluded from the evaluation metrics.

Measuring Standard Deviation

Analytical Standard Deviations:

- Gross Conversion = 0.0202
- Net Conversion = 0.0156

If the unit of analysis (denominator) and the unit of diversion (numerator) in an evaluation metric are different, the empirical variability will tend to be higher than the analytical variability. However, when they are the same the analytical estimate can be used. This is due to the fact that many distributions operate under the assumption of independence, but when units are different there is some uncertainty and correlation that is introduced, because there could be multiple cookies that are in fact the same user-id.

Both of the evaluation metrics chosen have different units of diversion (user-id) and analysis (cookie). Therefore, it would be best to compute the empirical variability for these metrics.

Sizing

Number of Samples vs. Power

No Bonferroni correction was used during the analysis phase, in which case the number of page views needed would be 685,325.

Duration vs. Exposure

Assuming 685,325 page views are required, if 90% of the traffic were diverted the experiment would take 20 days.

Ideally, less traffic would be diverted to the experiment just in case there was some sort of bug that it introduced. However, by diverting a higher fraction of traffic, a result with the confidence and power needed can be achieved more quickly, so the change can be rolled out (or not) in a more timely fashion. Luckily, the risk introduced by this experiment is relatively low, so we do not have to be too concerned about diverting this percentage of traffic. There is very little risk of anyone getting injured, and there is not any sensitive data being collected, in fact there is really no additional data being collected that was not already being collected. The main thing we would have to worry about this this proportion of traffic being diverted is a bug being introduced to the website, and hopefully this is something the Quality Assurance team would have found that before hand.

Experiment Analysis

Sanity Checks

Metric	Lower Bound	Upper Bound	Observed	Passes?
Number of cookies	0.4988	0.5012	0.5006	True
Number of clicks on “Start free trial”	0.4959	0.5041	0.5005	True
Click-through-probability on “Start free trial	0.0812	0.0830	0.0822	True

Result Analysis

Effect Size Tests

Metric	Lower Bound	Upper Bound	Statistical Significance	Practical Significance
Gross Conversion	-0.0303	-0.0108	True	True
Net Conversion	-0.0126	0.0028	False	False

Sign Tests

Metric	P-Value	Statistical Significance
Gross Conversion	0.0026	True
Net Conversion	0.6776	False

Summary

I did end up using a Bonferroni correction for the calculations, because we are using two evaluation metrics to try and make a decision and we need all the results of those metrics to match our expectations. When multiple comparisons are made, the probability of a rare event occurring becomes more likely. When we need all the results to be consistent with our expectations, the probability that one of the metrics leads us to the conclusion that we should fail to reject the null by chance is higher as well, raising our risk for type II error.

There are no discrepancies between the effect size or sign tests for these two metrics, which will help simplify the interpretation of the results in the upcoming recommendation.

Recommendation

Based upon these results, I would roll out the change to production. We were able to reject the first null hypothesis that there would be no change in the gross conversion, and we failed to reject the null hypothesis that there was no change in the net conversion as well. Both of these are in line of our original expectations of what needed to be observed to launch the test.

The results of the gross conversion test showed that there would be 3.03%-1.08% reduction in this metric, a statistically and practically significant result.

The results of the net conversion test showed that there would be a -1.26%-0.28% change in net conversion, which is neither practically nor statistically significant. However, it should be pointed out that given this confidence interval there is a chance that the change could cause a negative change of more than -0.75% (the practical significance boundary for this metric. If the actual impact did end up being more than -0.75%, this would be something that could be considered a negative impact given our initial expectations. All this being said, it is a risk that will just have to be weighed against the significant impact of reducing the gross conversion. My personal reasoning is that the chance of a smaller proportion of cookies becoming paying customers in the long run likely could not outweigh the resource benefit of having paid coaches spending fewer resource hours on non-paying customers. In reality other metrics and business expertise would help make the decision in a more informed manner.

Follow-Up Experiment

Based upon the results of this experiment, a logical next step would be to focus on how to reduce early cancellations (i.e. students giving up during the 14 day free trial, and cancelling their subscription). My guess would be that 14 days is not enough time for some people to make meaningful progress, in turn making them believe that they cannot learn anything meaningful with the paid subscription. However, if they were presented with the option to get their free trial extended 7 days when they go to cancel their account, that may give them the time they need to make meaningful progress and “get hooked”. The most obvious metric for examining whether or not the goal of reducing early cancellations was achieved would be retention (number of user-ids enrolled past the 14 day boundary / number of user-ids to complete checkout). In this case the metric would have to be altered slightly to make the comparison fair, and would be as follows: number of user ids enrolled past free trial period (14 or 21 days) / number of user ids to complete checkout.

Null Hypothesis: There is no difference in retention when the free trial period is 14 days, compared to when the free trial period is 21 days.

Alternative Hypothesis: There is an increase in retention when the trial period is changed to 21 days rather than 14 days.

For retention the unit of diversion is user-id and the unit of analysis is also user-id.

References

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