A/B Testing on Retargeting Ads Analysis

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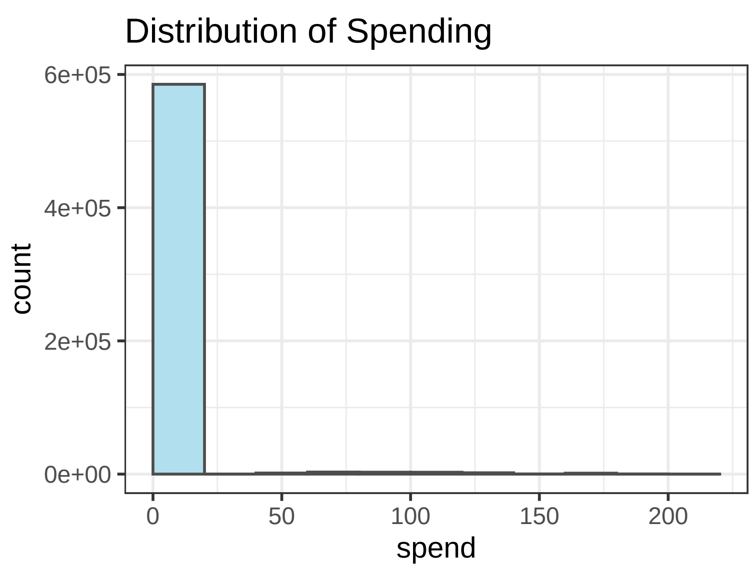
Overview

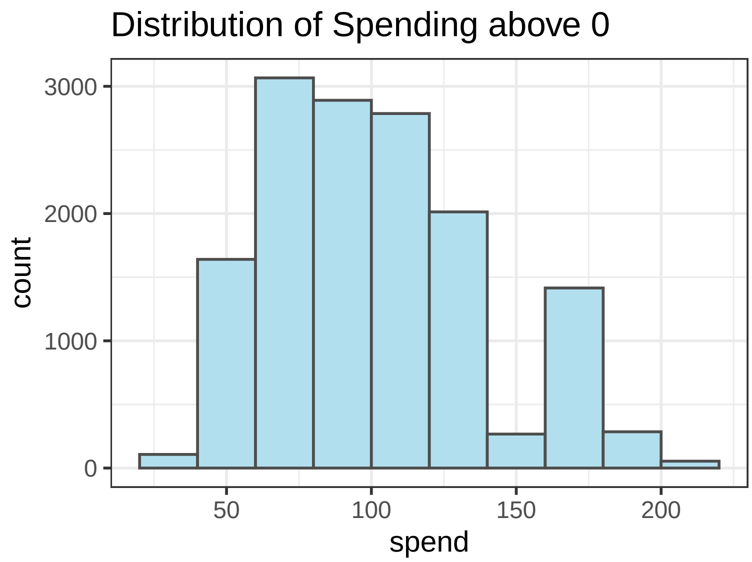
We randomly selected half of the customers for an A/B test. Treatment group customers were eligible for retargeting ads whereas control group customers were not. The A/B test result will be analyzed, and a optimal policy will be formulated to make sure that only customers with positive incremental effects will be retargeted by ads, and thus, we can get the highest profit from the campaign.

Check the A/B test validity

By inspecting the percentage of treatment group we can find that around half of the customers are in the treatment group. By checking the distribution of the URLs, we can also find that there's no obvious difference between treatment group and control group, so we can say that the A/B test is properly conducted.

Spend distribution and the average incremental effect of the retargeting campaign on spending

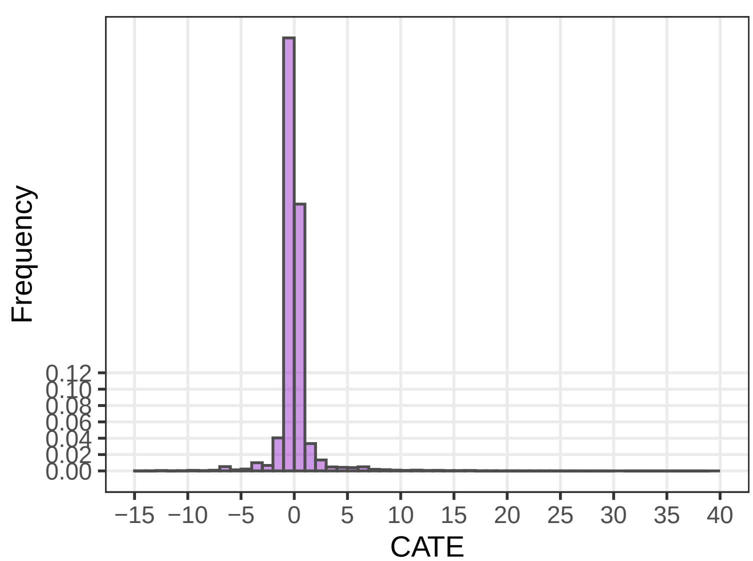




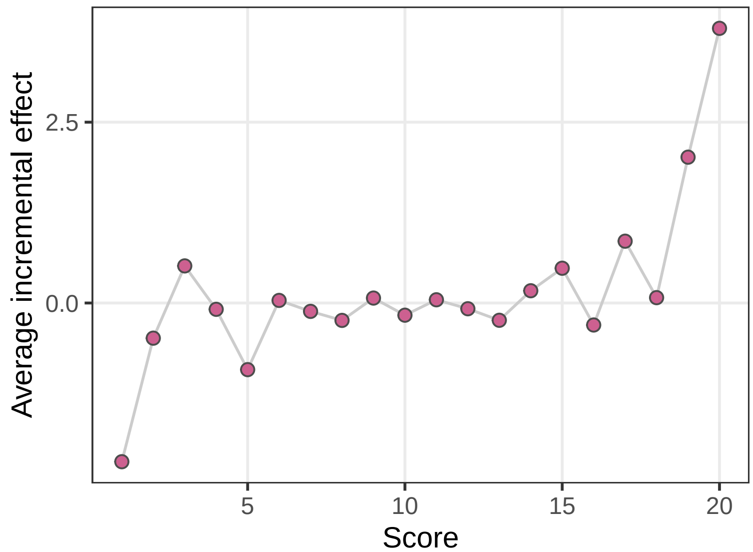
By checking the distribution of the spend, we can find that most customers don't have a spend but there are customers who has a very large spend. Overall, the average spend for treatment group is 2.58, the average spend for control group is 2.45, and the incremental effect of the retargeting campaign is 0.13. According to the t-test, the treatment group has a statistically significant lift compared to the control group. Therefore, it makes sense for the company to engage in retargeting. The incremental effect of the retargeting campaign differs from the average treatment of ad exposures because there are customers who are unreachable meaning that even though they are in the treatment group, they don't see the retargeting ads. We care about the incremental effect of the retargeting campaign because in reality, there are always customers who are unreachable.

CATE Analysis

The training sample is used to fit a two-in-one linear regression model, incorporating treatment_group and its interactions to estimate the effect of treatment on spending. The trained model is then applied to the test sample to predict spending under both treated and untreated conditions. The Customer-Level Average Treatment Effect (CATE) is computed as the difference between the predicted spending with treatment and without treatment for each customer, capturing the individualized impact of retargeting.



The distribution of the CATEs is shown above. It shows that the predicted customer-level incremental effects are highly heterogeneous, i.e. differ strongly across customers.



The predicted CATE is then converted into a lift graph. Most groups in the lift graph show no lift, while the last three groups have a high lift. This explains that the CATE prediction is valid as groups with higher scores have higher lift. We can see that because most customers don't have a spend, retargeting ads don't show much lift on them. However, there are a small amount of customers who show a large lift on the retargeting campaigns. This suggests that we should focus on them for the retargeting campaign to make a profit.

Develop an optimal personalized retargeting policy

By using the predicted CATE, we can formulate an optimal policy that only retargets customers when predicted incremental value is larger than retargeting cost. Then, the profit can be calculated.

	profit	perc_target
Optimal	973.638	0.232
None	893.387	0.000
All	836.267	1.000

By comparing the profits from the optimal policy, the policy that retargets no one and the policy that retargets everyone, we can find that the optimal policy has the highest profit. By retargeting only 23% of people who are able to give a positive incremental value, we don't need to spend a lot on the campaign but we can still get a high return.

Analyze the difference in spending by ads exposure

The average spend for customers who had ads exposure is 3.68, and the average spend for customers who didn't have ads exposure is 2.15. The difference is 1.53, which is much larger than the disparity between the overall retargeting campaign. Because bidding algorithms use detailed customer data, and high bids for customers with large predicted spending. Therefore, customers who saw ads are usually those with higher spend.

Re-evaluate bidding strategy and optimize the bid

The data can also be used to predict the maximum bid that the DSP algorithms should submit. We know that maximum bid should be $bid < margin \cdot ATT$. Therefore, maximum $bid = 0.37 \cdot 1.53 = 0.57$. We can also predict customer level ad exposure effect by applying the similar method like CATE, but this time use impression interactions as independent variables. Then, calculate the customer-level maximum bid as $margin \cdot cATT$.

Summary Slides

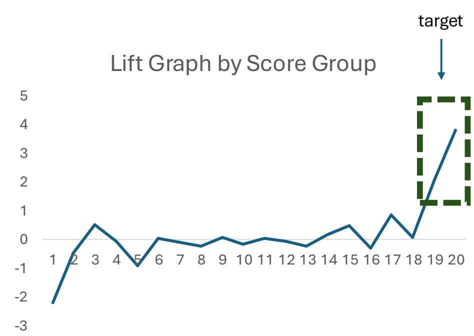
Retargeting Campaign Optimization

Objective:

- Conduct an A/B test to evaluate the impact of retargeting ads on customer spending.
- Develop an optimal policy to maximize profit by targeting customers with positive incremental effects.

Why we need an optimized retargeting campaign?

- We had a statistically significant lift of $0.13 from retargeting ads.
  - Average spend:
    - Treatment group: $2.58
    - Control group: $2.45
- Customer-Level Average Treatment Effect (CATE) analysis shows only a small segment of customers responds strongly to retargeting.



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Retargeting Campaign Optimization (continued)

How to apply the optimal retargeting campaign?

Retarget only customers with predicted positive incremental value exceeding ad cost.

Predicted Results

The optimal policy achieves the highest profit with minimal spend.

Policy	Profit	Targeting Percentage
Optimal policy	$ 973.64	23%
No Retargeting	$ 893.39	0
Retargeting all	$ 836.27	100%

Conclusion

- Retargeting is effective but should be applied selectively.
- Optimized policies significantly increase profit while reducing unnecessary ad spend.
- Further fine-tuning of bidding strategies can enhance efficiency and returns.

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