

# **Creative Gaming**

## **Uplifting model**

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# Introduction to the Problem

- Background: Creative Gaming's "Space Pirates" achieved initial success on iOS platforms, introducing multiplayer console gaming to mobile.
- Zalon Campaign Adoption: Priced at \$14.99 with only 5.75% of active players purchasing within the first two months.
- Market Overview: The video game industry was valued at \$66.7 billion in 2019, with mobile gaming reaching \$70 billion by 2018.
- Monetization Challenges: Balancing in-app purchases to retain engagement without alienating users, leveraging telemetry data for strategic decisions
- Challenge:
  - Maintaining user engagement and revenue over time with a monetization strategy that balances free and paid content.
  - Low Adoption Rate of the Zalon Campaign
  - Pricing and Awareness Issues
  - User Engagement and Retention
  - Market Positioning and Awareness

# Problem Statement and Approach

- Optimizing Customer Targeting: Employing uplift modeling to identify customers who are most likely to be influenced by the marketing campaign for the Zalon campaign, thus improving the precision of targeting efforts.
- Maximizing Incremental Profits: By accurately identifying and targeting the segment of the user base that will provide the highest incremental profits, the strategy aims to make the most efficient use of marketing resources.
- Refining Marketing Strategies: The approach seeks to refine marketing strategies based on insights derived from uplift modeling, thereby addressing the core issues of user engagement, pricing strategy, and campaign awareness effectively.

# Building Uplifting Model:

Goal: Leverage uplift modeling to select optimal customers for Zalon campaign targeting.

Data Utilized to build the uplift model using Logistic regression:

Control Group (Group 1): cg\_organic\_control (30,000 customers not exposed to ads).

Experimental Group (Group 2): cg\_ad\_random (30,000 customers that were exposed to ads).

Calculate the uplift score: computed as  $\text{pred\_treatment} - \text{pred\_control}$ .

Uplift tab: Includes an incremental\_resp column, which indicates the number of incremental purchases made when customers up to that particular n-tile were targeted with the ad.

Calculate Uplift Metrics: Calculate the Uplift (%) and Incremental Uplift (%) across 20 deciles

This means you will segment the population into 20 equally sized groups based on their uplift scores.

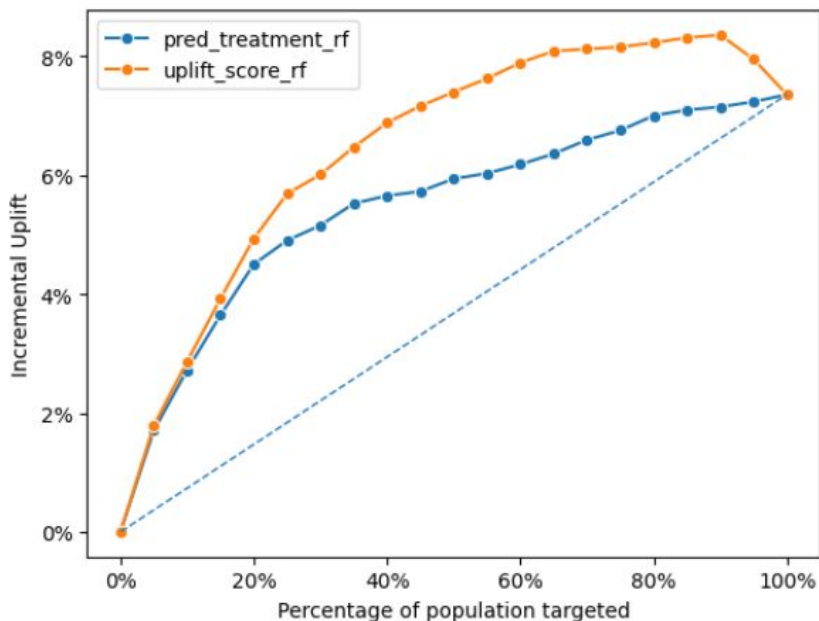
Profit Calculation: Calculate expected incremental profit when targeting the top 30,000 customers out of a total of 120,000 customers using the predictions from an uplift model.

We achieved a total profit of \$46,861.43, which represents the expected incremental profit from targeting the best 30,000 customers using the uplift model.

# Propensity vs Uplift

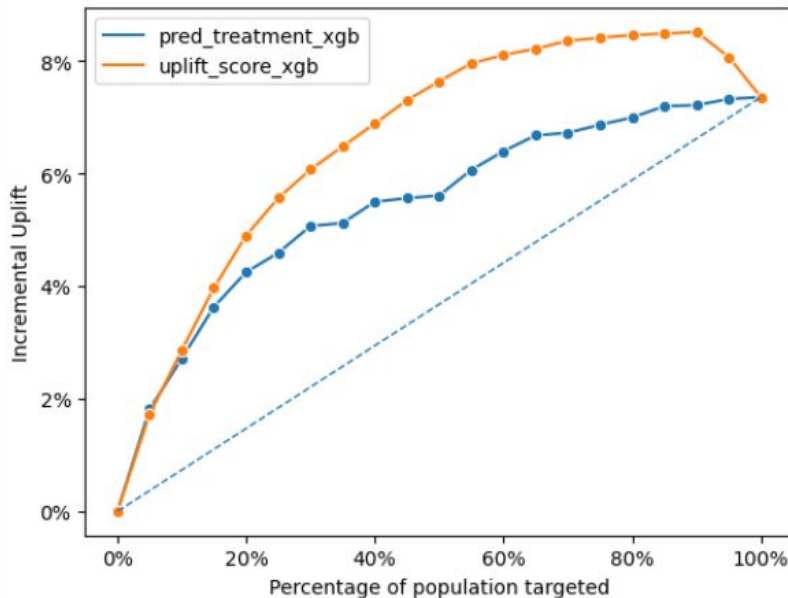
- Propensity models are trained exclusively on data from the group that received the ad campaign.
- These models cannot capture the natural response behaviors that would occur in the absence of the ad.
- As a result, they do not account for the organic actions of customer segments.
- This leads to an underestimation of the true incremental uplift attributed to the ad campaign.
- The last decile, likely consists of the 'Do-Not-Disturb' individuals. In contrast, the uplift model is capable of identifying this negative impact, as evidenced by the negative uplift recorded when targeting this particular group.

# Random Forest model



- Performed Gridsearch for both treatment as well as control data with the best hyperparameter choices max\_depth and n\_estimators.
- Performed on correctly predicted data on OOB samples taken for validation.
- Treatment group AUC -> 0.7
- Control group AUC -> 0.8
- Uplift increases with more targeting initially, indicating campaign effectiveness. Consists of Persuadables.
- After reaching a peak, the uplift plateaus and declines, especially for the uplift score.
- Early segments respond well to the campaign, but later segments show less response.
- 'Sure Things,' 'Lost Causes,' and 'Do-Not-Disturb' are likely in the less responsive segments.

# Xgboost model



- Performed Gridsearch for both treatment as well as control data with the best hyperparameter choices max\_depth, min\_child\_weight, gamma (regularization).
- Treatment group AUC -> 0.78
- Control group AUC -> 0.88
- Uplift increases with more targeting initially, indicating campaign effectiveness. Consists of Persuadables.
- After reaching a peak, the uplift plateaus and declines, especially for the uplift score.
- Early segments respond well to the campaign, but later segments show less response.
- 'Sure Things,' 'Lost Causes,' and 'Do-Not-Disturb' are likely in the less responsive segments.

# Evaluating Profit and Incremental Profits

## To maximize profit

Propensity Predicted Probability  
> Breakeven

## To Maximize Incremental Profits

Predicted uplift > Breakeven

Model	Optimum Percentage to Target	Nearest 5th Percentile
Logistic uplift	22.4%	20%
Logistic Propensity	47.25%	45%
Random Forest uplift	30.4%	30%
Random Forest Propensity	50.25%	30.4%
XGBoost uplift	26.3%	25%
XGBoost Propensity	55.1%	55%



# Conclusion

1. Precision in Targeting: Uplift modeling assesses the specific impact of marketing campaigns on individual behavior, differentiating between those influenced by the campaign and those who would have responded favorably regardless. This ensures more effective utilization of resources.
2. Efficiency in Marketing: By identifying and excluding "sure things" and "lost causes," uplift modeling focuses on "persuadables," thereby reducing wasteful expenditure and maximizing campaign effectiveness.
3. Cost-Effectiveness: The focused approach of uplift modeling minimizes costs by targeting only those individuals likely to be swayed by the campaign, enhancing the overall return on investment.

# Conclusion and Results

4. Enhanced Outcomes: Through its ability to accurately pinpoint the impact of marketing interventions, uplift modeling leads to improved marketing outcomes compared to propensity models, which cannot discern the influence of natural inclinations versus the impact of advertising.

Model	Uplift Profit	Propensity Profit
Logistic Model	3,450.67	648.654
Random Forest	4,056.86	1,367.00
XGboost	4,066.39	715.52

**Thank you!**