# Enhancing Targeted Marketing Strategies: Interpretable Uplift Modeling to Identify Key Client Segments

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# Abstract

Uplift modeling stands at the forefront of machine learning innovation, serving as a pivotal tool for quantifying the causal effect of marketing strategies on consumer decisions. This paper explores the intricacies of uplift modeling, examining its theoretical framework and the practical application of its principal methodologies: the one-model, two-model, and class transformation techniques. Through an empirical study of a Portuguese bank's direct phone marketing campaigns, we aim to discern the predictive capability of uplift modeling in determining client engagement with term deposit subscriptions. We present a detailed comparative analysis of the uplift modeling techniques, scrutinizing their effectiveness and limitations within the context of our dataset. The findings reveal that the class transformation approach, specifically using CatBoost, significantly outperforms its counterparts, providing a marked increase in predictive accuracy and customer conversion rates. This insight emphasizes the potential of uplift modeling to identify key customer segments for targeting, enhancing the precision and ROI of marketing initiatives. Our study contributes to the expanding literature on causal inference and targeted marketing, providing a pathway for businesses to fine-tune their marketing strategies. The application of the uplift models detailed in this paper transcends the scope of banking, offering a versatile framework for various industries to deploy data-informed decisions, thereby fostering revenue growth and optimizing marketing expenditures.


# Introduction

Uplift modeling has become an increasingly favored technique in machine learning, aimed at gauging the direct effects of marketing actions on customer responses. It operates on a range of methodologies such as the single model, dual model, and class transformation. The single model method, a straightforward approach, predicts outcomes based on treatment indicators and covariates, but it may miss the subtleties of varying customer responses [1]. The dual model strategy uses separate models for treated and control groups, enhancing accuracy but at the cost of increased computational demands and data requirements [2]. The class transformation technique redefines the problem into a new binary classification, adaptable to standard algorithms, though its effectiveness is subject to the algorithm selection and data preprocessing [2]. In our study, we compare these methodologies, applying them to a dataset from a Portuguese bank's telephone marketing efforts to predict term deposit subscriptions. This dataset, drawn from the UCI Machine Learning Repository, includes client demographics, campaign interactions, and subscription outcomes, spanning 41,188 records and 20 variables, as detailed in Moro (2014) [3]. To assess the models, we employ metrics like the *Qini curve, response rate, and uplift at k* [4], and we also dissect model efficacy across distinct customer categories—*Sure things, Lost causes, 'Persuadables', and Sleeping Dogs* [5]. This nuanced analysis enables the pinpointing of key segments for targeted marketing, enhancing campaign ROI—a principle elaborated by Radcliffe & Surry's (1999) [6]findings. In essence, uplift modeling offers a robust framework for understanding and optimizing the causal influence of marketing strategies on consumer behavior, guiding businesses to tailor their approach for maximum impact in the competitive terrain of data-driven marketing.

The primary objective of this research is to develop a comprehensive uplift model that accurately quantifies the efficacy of current marketing campaigns against a baseline of random chance. This model aims to classify customers into four distinct categories: *Persuadables, Sure Things, Sleeping Dogs, and Lost Causes*. The categorization is designed to enable the strategic tailoring of future marketing initiatives, ensuring optimal engagement and conversion. Through this predictive analytical framework, we aim to enhance the precision of target marketing, thereby maximizing the return on investment for similar campaigns in subsequent applications.

# Literature Review

Uplift modeling is a method that's becoming increasingly popular for analyzing how marketing campaigns influence customer actions. It's a blend of causal inference and machine learning, offering a way to measure the specific impact of a campaign. The concept was first introduced by Radcliffe & Surry in 1999[6], focusing on the incremental responses in marketing. Since then, the field has evolved with new methods like Lo's two-model approach in 2002[7], which involves a separate analysis of treatment and control groups, and the class transformation technique by Gutierrez and Gabor in 2016[8], transforming the uplift question into a classification problem. Different customer segments like *'sure things,' 'lost causes,' 'sleeping dogs,'* and '*persuadables*' have been identified, each with unique responses to marketing campaigns. Verbraken et al. (2012)[9] suggested that specifically targeting '*persuadables'* with tailored offers could significantly boost campaign responses, while focusing on *'sure things'* might enhance customer retention. Recent studies have tested various uplift models, often finding the two-model approach superior. However, as research by López et al. [10]and Olaya, Coussement, and Verbeke (2020) [11] shows, no single method works best in every situation—it really depends on the specific campaign and goals. Uplift modeling has been applied in many areas, from healthcare—predicting patient treatment responses [12]—to e-commerce—optimizing ad placements[13], proving its versatility in enhancing marketing effectiveness and boosting ROI.

# Methodology

*Dataset*

The datasets in question originates from direct marketing campaigns conducted by a Portuguese banking institution, utilizing phone calls as the primary communication channel. The aim was to discern whether potential clients would subscribe to a bank term deposit, a process that occasionally necessitated multiple phone calls per client. This research utilizes four distinct datasets: the comprehensive 'bank-additional-full.csv' with 41,188 instances and 20 attributes, chronologically sorted from May 2008 to November 2010—paralleling the analysis by Moro et al. in 2014[3]; a smaller subset 'bank-additional.csv' containing a random 10% sample of the former; the 'bank-full.csv' with all examples yet with 17 attributes, reflecting an earlier version with fewer attributes; and 'bank.csv', which is a 10%

random sample of the 'bank-full.csv'. The pivotal classification objective is to predict the client's likelihood of subscribing to a term deposit, denoted by the binary variable 'y'.

*Data Analysis*

The data analysis was conducted in the following sequence: Initially, we embarked on exploratory data analysis (EDA) to gain an understanding of the data's characteristics. Next, we undertook feature engineering to craft relevant variables for modeling. This was followed by the development of a base model to establish a benchmark for comparison. After that, we moved on to feature importance and understanding, where we examined the influence of individual features on the model's predictions. Finally, we applied uplift modeling techniques to quantify the impact of the marketing strategies on customer behavior.

The primary focus of EDA is to discern patterns and actionable insights that could potentially enhance the effectiveness of future campaigns, specifically through the lens of subscription rates to bank term deposits. In machine learning, feature engineering is a crucial step that involves transforming raw data into features that better represent the underlying problem to the predictive models, resulting in improved model accuracy on unseen data. For the banking campaign datasets, this included binning age, day, and month variables to capture trends across different life stages, weekdays, and seasonal patterns respectively, thus enhancing the model's interpretability and performance. One-hot encodingwas applied to other categorical variables, which converted categorical data into a numerical format by creating binary columns for each category. This is essential because most machine learning algorithms require numerical input. Finally, standard scaling was employed on numerical variables to normalize their range, ensuring that each feature contributed equally to the prediction process thereby improving algorithm convergence. These steps were vital to prepare the data for modeling, particularly when using algorithms sensitive to feature scales or distribution. The base models we used included 7 models (Logistic regression, Random forest, Decision tree, XGboost, k nearest neighbors, multi-layer perceptron (MLP),and Catboost algorithms) and we tuned 21 various hyper parameters (finding the optimal set of values). For interpretability, we implemented a SHAP model. SHAP(SHapley Additive exPlanations) models provide a powerful framework for feature understanding in machine learning. It leverages the concept of game theory to assign an importance value to each feature, reflecting its contribution to the prediction. This method ensures consistency and local accuracy by considering all possible combinations of features' interactions. With SHAP values, one can interpret the model's decision-making process on an individual prediction basis, which is particularly beneficial in complex models like deep learning or ensemble methods.

*Uplift Modelling Approaches*

Uplift modeling has become a popular technique in machine learning for estimating the causal impact of marketing interventions on customer behavior. There are several methodologies for uplift modeling, including the one-model approach, the two-model approach, and the class trans- formation technique.

The one-model approach is the simplest method for uplift modeling, using a single model to predict the outcome variable as a function of the treatment indicator variable and other covariates. The model can be expressed as:

$Y = f(W, X, \theta) + \epsilon$ (1)

where Y represents the outcome variable (e.g., purchase, click, etc.), W is the treatment indicator variable, X is a vector of covariates (e.g., age, gender, etc.), $f$ is a model function (e.g., linear regression, logistic regression, decision tree, etc.), θ represents the model parameters, and $\epsilon$ is the error term.

The one-model approach estimates the treatment effect as the difference in the expected outcome when the treatment indicator variable W changes from 0 (control) to 1 (treatment), keeping the covariates X constant. The treatment effect can be calculated as:

$\Delta Y = f(1, X, \theta) - f(0, X, \theta)$ (2)

where ΔY represents the estimated uplift or treatment effect for a given set of covariates X. Note that the specific model function $f$ will depend on the method chosen for uplift modeling.

The two-model approach employs separate models for the treated and control groups to predict the outcome variable. The models can be expressed as:

$Y_t = f(W = 1, X, \theta_t) + \epsilon_t \; Y_c = f(W = 0, X, \theta_c) + \epsilon_c$ (3)

where $Y_t$ and $Y_c$ are the outcomes for the treated and control groups, respectively, $\theta_t$ and $\theta_c$ are the model parameters for the treated and control groups, respectively, and $\epsilon_t$ and $\epsilon_c$ are the error terms.

The treatment effect can be estimated as the difference between the expected outcomes for the treated and control groups, given a set of covariates X:

$\Delta Y = f(W = 1, X, \theta_t) - f(W = 0, X, \theta_t)$ (4)

The two-model approach may yield more accurate results than the one-model method, but it can also be more computationally intensive and may require larger datasets to achieve the desired level of accuracy. The class transformation technique involves modifying the outcome variable to create a new binary classification problem. This transformed problem can then be solved using standard classification algorithms, such as logistic regression or decision trees. The class transformation can be expressed as:

$Z = WY + (1 - W)(1 - Y)$ (5)

where Z is the transformed outcome variable and takes on values of 0 or 1, depending on whether the individual responded positively or negatively to the treatment, respectively.

The transformed problem can be represented as a binary classification problem with the response variable Z defined as:

$Z = \{1, \text{ if } Y_1 > Y_0, 0, \text{ otherwise}\}$ (6)

where $Y_1$ and $Y_0$ represent the potential outcomes under treatment and control, respectively. Once the transformed problem is created, standard classification algorithms such as logistic regression or decision trees can be applied to estimate the probability of a customer belonging to the treatment group. The estimated probability can then be used to calculate the treatment effect for each customer.

$\Delta Y = E(Y_1 - Y_0|Z = 1) \times P(Z = 1) + E(Y_0 - Y_1|Z = 0) \times P(Z = 0)$ = Uplift for treated × Response rate + Uplift for control × (1- Response rate) (7)

where $E(Y_1 - Y_0|Z = 1)$ and $E(Y_0 - Y_1|Z = 0)$ represent the expected uplift for the treated and control groups, respectively, and $P(Z = 1)$ and $P(Z = 0)$ represent the probabilities of belonging to the treatment and control groups, respectively.

# Results

Initial exploratory data analysis revealed that among the contacts who responded positively to the treatment, 18% had a history of conversion from past campaigns. A notable 34% of the successfully converted contacts fell within the age bracket of 35 to 50 years, and a significant majority of 63% did not have a housing loan obligation (refer to Fig. 1). Additionally, the data indicated that, on average, individuals in the converted group had a higher bank balance compared to those who did not convert.

The analysis demonstrated that Catboost and XGBoost outperformed other models in terms of both recall (Fig. 2a*)* and accuracy (Fig. 2b), indicating their superior capability in predicting conversions as well as non-conversions effectively.

The application of the SHAP model to analyze marketing data from a Portuguese bank identified five critical features that impacted a client's decision to subscribe to a bank term deposit, as shown in Fig. 3. The possession of a cellular phone stood out as a significant factor, emphasizing the role of communication access in influencing decisions. Additionally, a client's bank balance highlighted the impact of financial health on their choices. A history of subscribing to products suggested that brand loyalty and customer satisfaction were key drivers of future transactions. The presence of a housing loan indicated a client's financial obligations and their willingness to take on new financial products. Furthermore, the interval since the last interaction with a campaign underscored the importance of strategic timing and persistence in marketing efforts. These findings provided valuable directions for tailoring future marketing campaigns to be more targeted and effective.

The Class Transformation_Cat model achieved the highest uplift at 30% of all three models. The SoloModel_XGB and TwoModels_XGB models achieved lower uplift values of 24%and 25%, respectively *(*Fig. 4*).* Figure 5 shows uplift score results in form of percentile distribution and response rate distribution. Treatment group showed a variance, but generally higher response rate compared to the control group, which is consistent with the expected outcome of a successful uplift modeling campaign.

# Discussion

Through an empirical study of a Portuguese bank's direct phone marketing campaigns, we aim to discern the predictive capability of uplift modeling in determining client engagement with term deposit subscriptions. We present a detailed comparative analysis of the uplift modeling techniques, scrutinizing their effectiveness and limitations within the context of our dataset. The utilization of the SHAP model in analyzing the CatBoost model has uncovered critical insights into customer behavior, particularly in the domain of term deposit subscriptions. The model's interpretive strength lies in its capacity to highlight features that substantially impact customer decision-making. For instance, the ownership of a cellular phone is not merely a conduit for communication but a significant predictor of customer engagement, as our analysis reveals that individuals with readily available contact means are more receptive to marketing initiatives [14].

Furthermore, the importance of a client's bank balance as a predictor of investment in term deposits resonates with Qingyang Chen's (2023) [5]assertion of financial health as a bedrock of investment behavior. This revelation prompts a deeper examination of how financial institutions can align their products with the economic profiles of their clients. Similarly, the influence of brand loyalty, as evidenced by previous product subscriptions, echoes Sérgio Moro's (2021)[15] findings on the significance of customer relationship history in forecasting future engagement.

The relationship between housing loans and financial behavior, alongside the optimal timing of contact as determined by days since the last campaign interaction, reflects a nuanced understanding of client circumstances and their receptivity to new financial products. This dual factor of financial commitments and engagement timing has been corroborated by Tingyu Wu et al. (2023)[16], who emphasized the delicate balance of persistence and timing in customer conversion success.

In this study, we employed several uplift modeling techniques, including the Single Model approach, Two Model approach, and the Class Transformation technique, to predict customer conversion. The models were evaluated based on their uplift percentages, providing insights into their effectiveness in increasing the likelihood of conversion. The Class Transformation_Cat model outperformed other configurations, achieving the highest uplift at 30%. This indicates a significant improvement in conversion rates when this model is applied.

The impact of choosing the appropriate uplift modeling approach on the success of marketing campaigns in increasing conversions is substantial, as evidenced by our findings. This aligns with prior research that emphasizes the importance of uplift modeling in targeted marketing efforts. For example, López et al. (2021) [10]demonstrated the application of Single Model, Two Model, and Class Transformation techniques, including CatBoost, for customer conversion prediction, highlighting the practical implications of these techniques in marketing. Comparing our results with existing studies, our research emphasizes the effectiveness of the Class Transformation_CatBoost model in driving customer conversions.

Further supporting the effectiveness of the Class Transformation_CatBoost model in driving customer conversions, Rudas and Jaroszewicz (2018)[17] showcased the model's potential in optimizing marketing strategies and resource allocation. This is complemented by the work of Gutierrez and Gérardy (2017)[8], who provided a comprehensive review of causal inference and uplift modeling, offering a framework for understanding the impact of different modeling techniques on marketing outcomes.

The variations in uplift percentages across different models provide essential insights into the incremental impact of treatments on customer behavior, a critical consideration for decision-makers aiming to maximize the effectiveness of their marketing initiatives. The study's findings highlight the need for businesses to invest in advanced modeling techniques for precise customer targeting, especially in highly competitive markets. The effectiveness of the Class Transformation_CatBoost model in particular points towards its potential in enhancing the precision of targeting and overall campaign performance.

## Conclusion

In conclusion, this research emphasizes the significant potential of uplift modeling in enhancing customer conversion rates. Among the tested models, the Class Transformation_CatBoost model stood out, achieving a remarkable 30% increase in conversions. This underscores uplift modeling's transformative impact on targeted marketing, potentially boosting customer engagement and business revenues. We advocate for the broader application and exploration of uplift modeling across various industries. Future research should aim to pinpoint specific customer segments that benefit most from these techniques and assess the long-term effects on customer loyalty and retention for a comprehensive evaluation of their effectiveness. For practical application, we encourage businesses to incorporate uplift modeling into their marketing analytics to refine campaign accuracy, minimize costs, and build deeper customer connections. Further, fostering partnerships between academia and the industry could spur the development of advanced uplift modeling approaches tailored to address real-world business challenges.

However, this study is not without its limitations, including challenges with data imbalance and the dependence on the data's quality and scope, which could influence model performance and the accuracy of uplift estimates. Additionally, the exclusive focus on uplift modeling might overlook other influential factors on conversion rates, such as market trends and customer sentiment. The applicability of our findings may also vary across different sectors and market conditions, highlighting the need for cautious application and further validation in diverse settings. Thus, while our findings contribute valuable insights into the use of uplift modeling for customer conversion, it's crucial for both researchers and practitioners to recognize these limitations and approach the interpretation and application of these results with care in real-world contexts.

## Declarations

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# Author Contribution

Toyosi Bamidele - Texas Tech University, United StatesUchenna Mgbaja - Norquest College, CanadaAll authors reviewed the manuscript.

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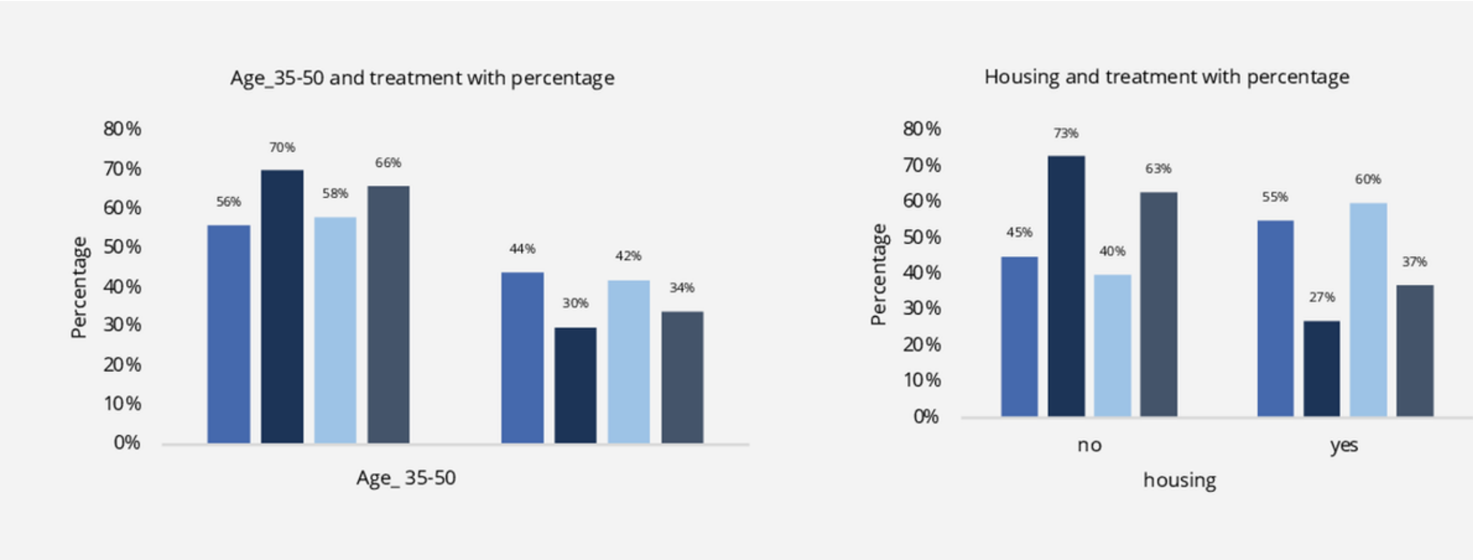
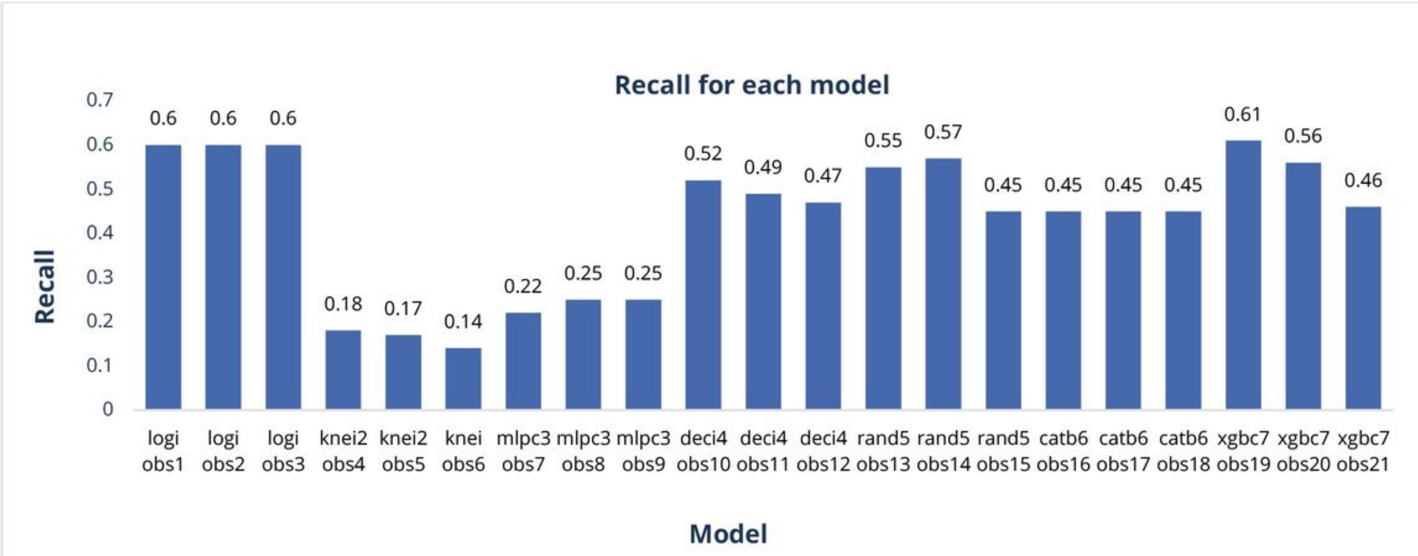
# Figures

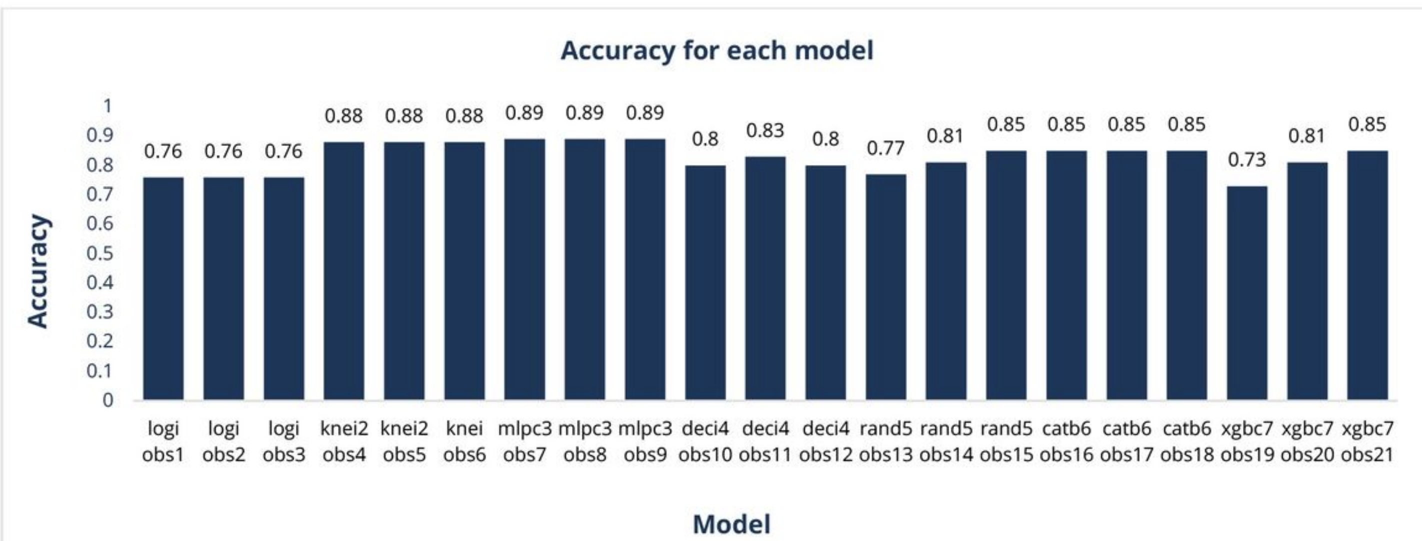



## Figure 1

*Data Visualization for preliminary data analysis* a.

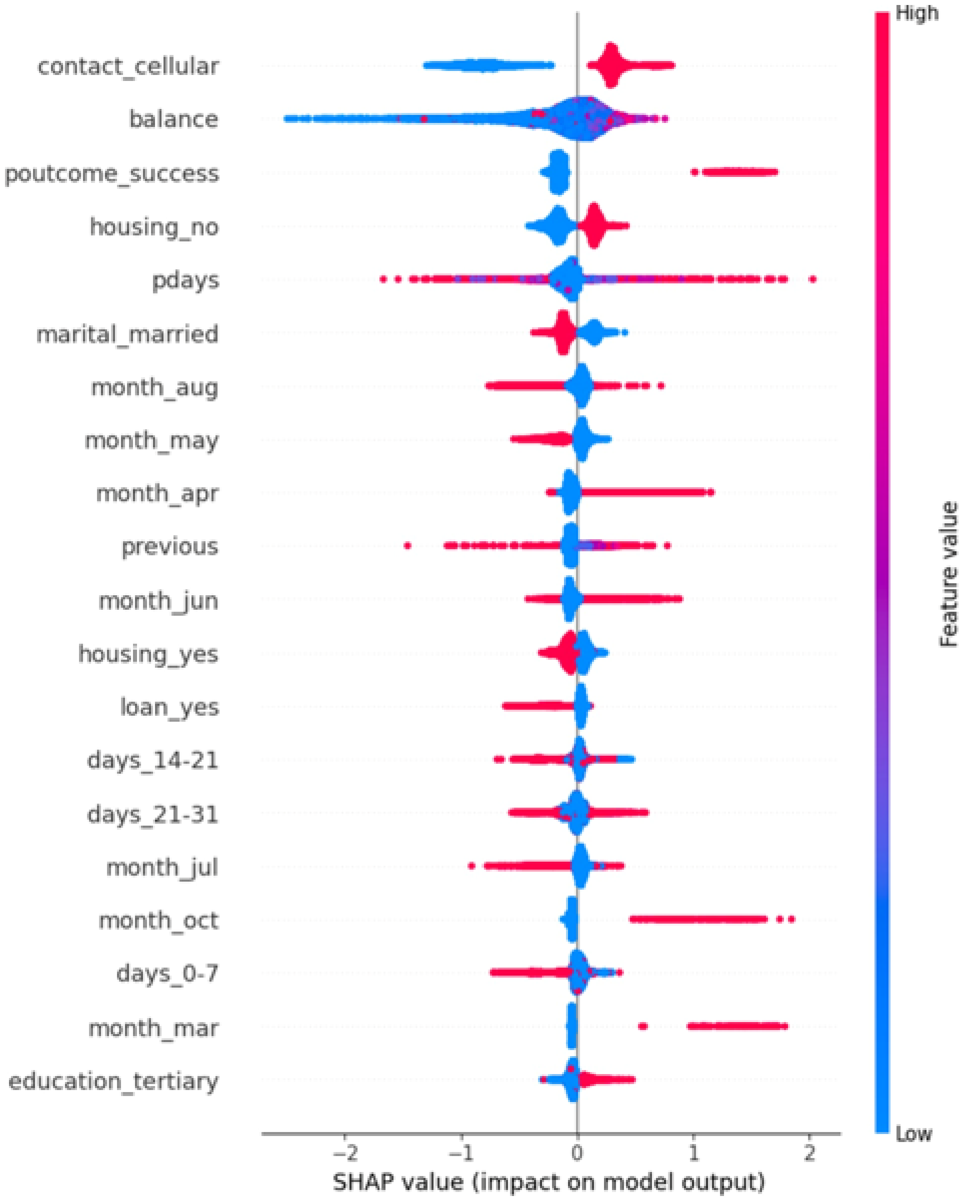



b.




## Figure 2

*Base model classification. a. represents recall scores. b. represents accuracy scores. Here “logi” ,”knei”, “mlpc”,”deci”, “rand”, “catb”,and “xgbc” represent logistic regression, k nearest neighbors, multi-layer perceptron, Decision tree,  Random forest , Catboost , and XGboost respectively.*




## Figure 3

*SHAP values (impact on model output)*

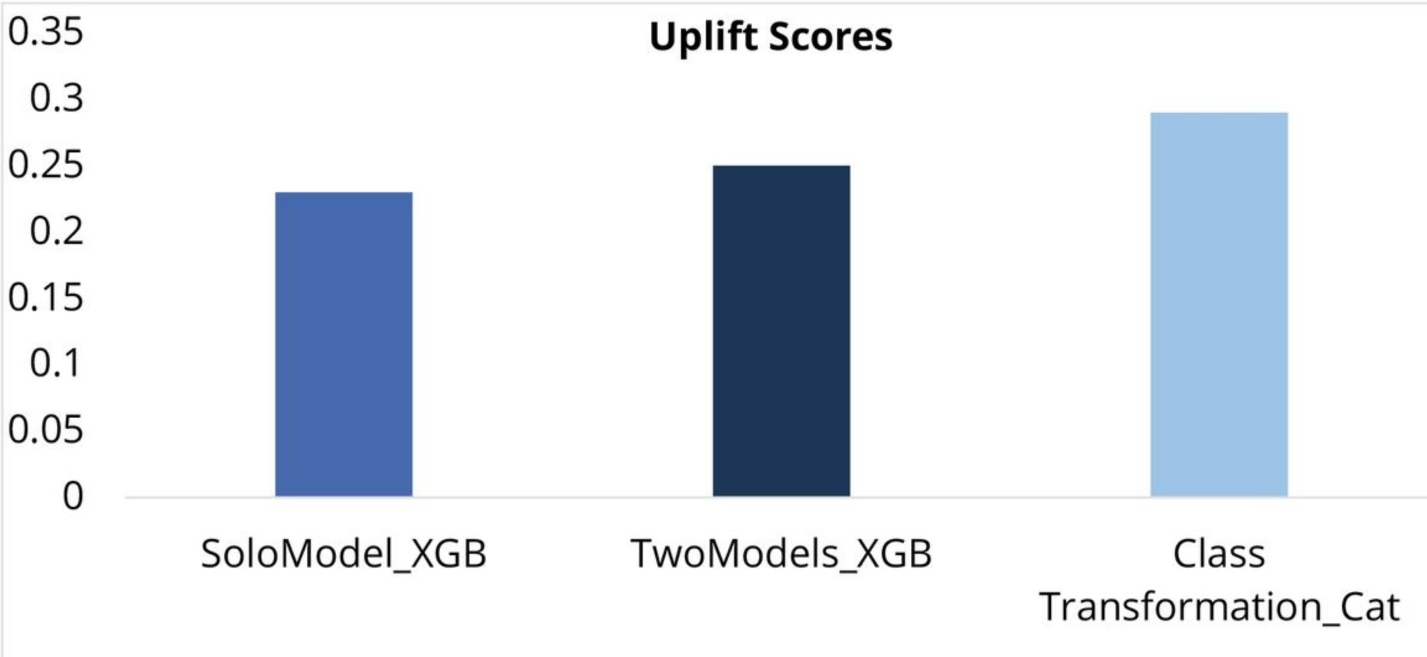



Figure 4

*Uplift scores*

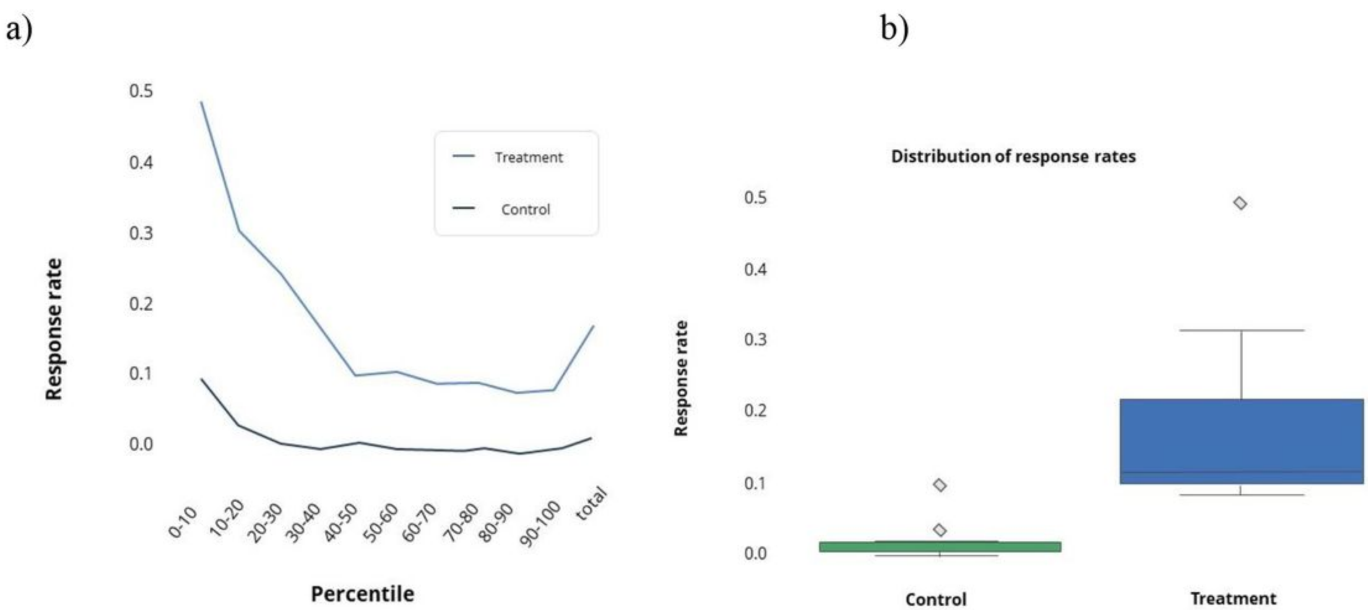



Figure 5

*a. Percentile distribution of treatment and control group response rate. b. Treatment vs. control group response rate distribution.*