

# Predicting the Success of Bank Telemarketing

By:

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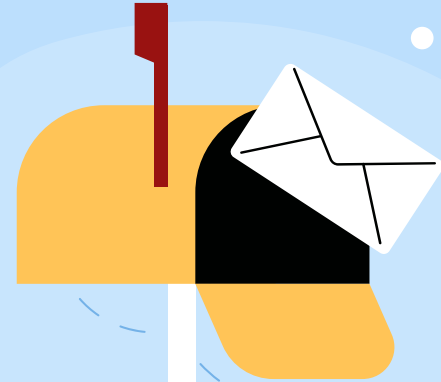
Ruiqi Jiang

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# 01. Background



# Problem Definition & Data Source

<i>Demographic Information</i>	<i>Business-related features</i>
Job	Contact
Marital	day_of_month
Education	month
Default	p_outcome
Housing	duration
loan	campaign
age	pdays
balance	previous

This dataset pertains to banking marketing initiatives conducted by a bank in Portugal.

The objective of this classification task is to predict **whether a client will opt in ('yes') or opt out ('no') of a term deposit (denoted as variable y).**

Data Source: [Bank Marketing - UCI Machine Learning Repository](#)

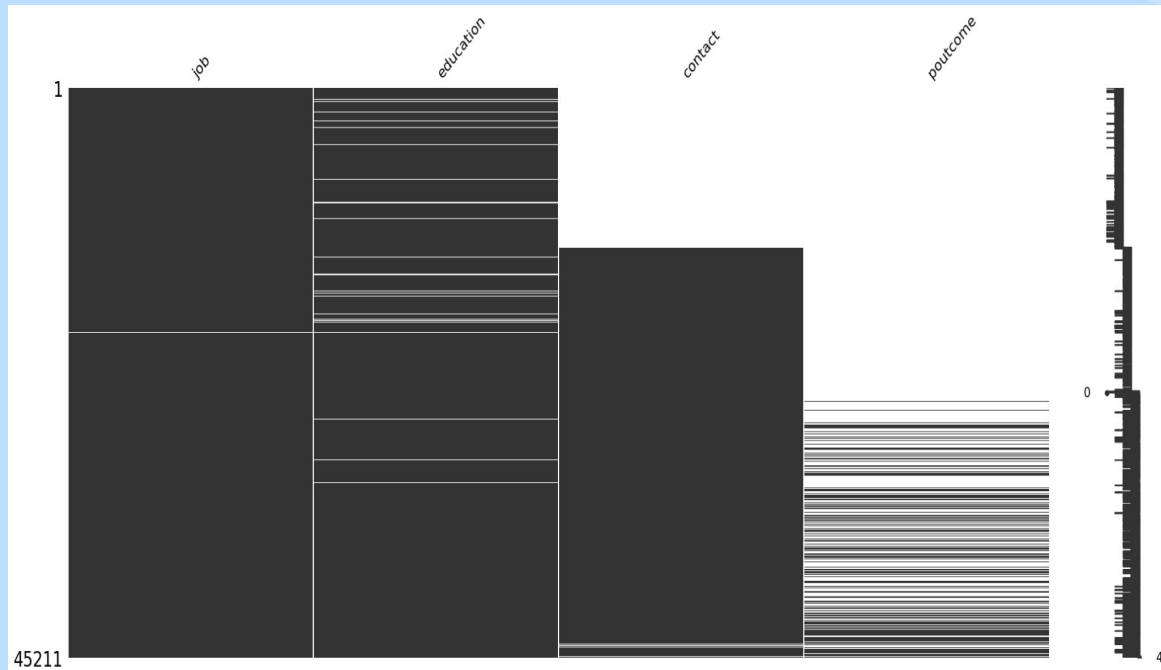
# 02. Data Exploration



# Data cleaning

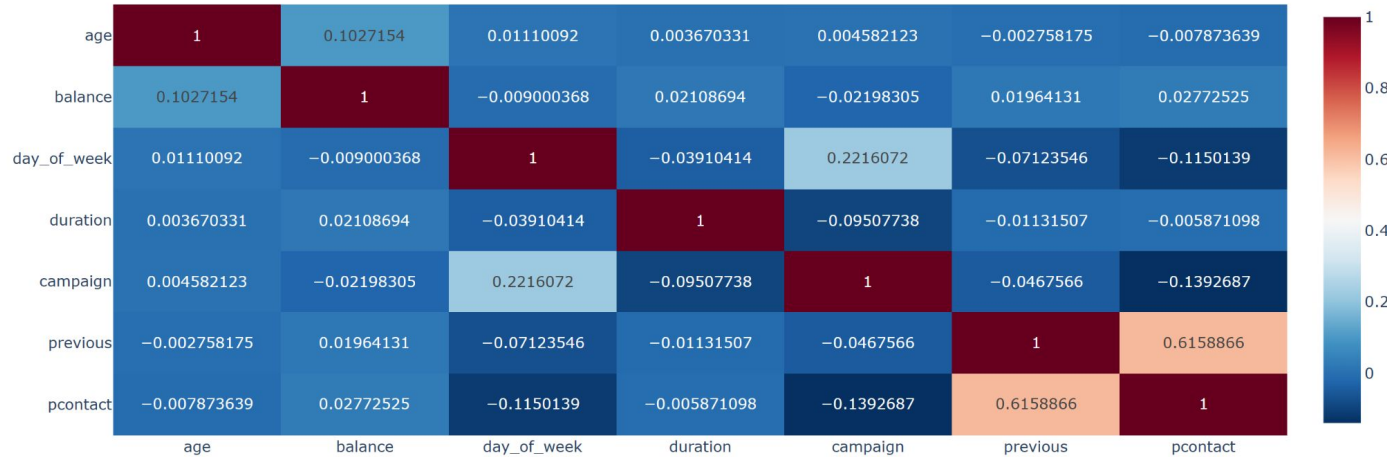
If null value has no analytical meaning and can not be converted, we drop rows with null (job, education, contact);

If null value can be converted meaningfully, we replace any value except success to failure (poutcome).



# Data Exploration

Heatmap of Correlation Matrix

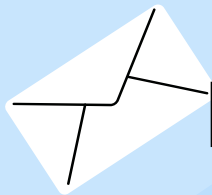


Low Dependence & Correlation between Numeric Features

## 03. Modeling

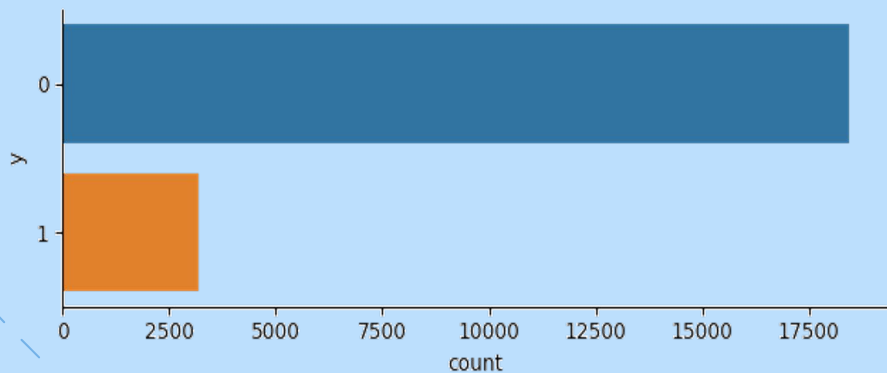






# Dealing with imbalanced data

Since imbalanced dataset leads to model bias and misleading metrics, we applied the Adaptive Synthetic Sampling on the training dataset.



Class imbalance in training dataset

	TRAIN (70%)		TEST (30%)	
Successful? (Y/N)	Y	N	Y	N
Before ADASYN	3186	18448	1327	7946
After ADASYN	18641	18448	1327	7946



# Stacking System Design

## Why Stacking System?

Aggregate 4 base models with **different underlying assumptions** and **strengths** to make more informed predictions.

### Stacking System with Four Base Model Candidates:

- Logistic Regression
- Support Vector Machine
- Decision Tree
- Gradient Boosting Model

**Meta Classifier: Random Forest**

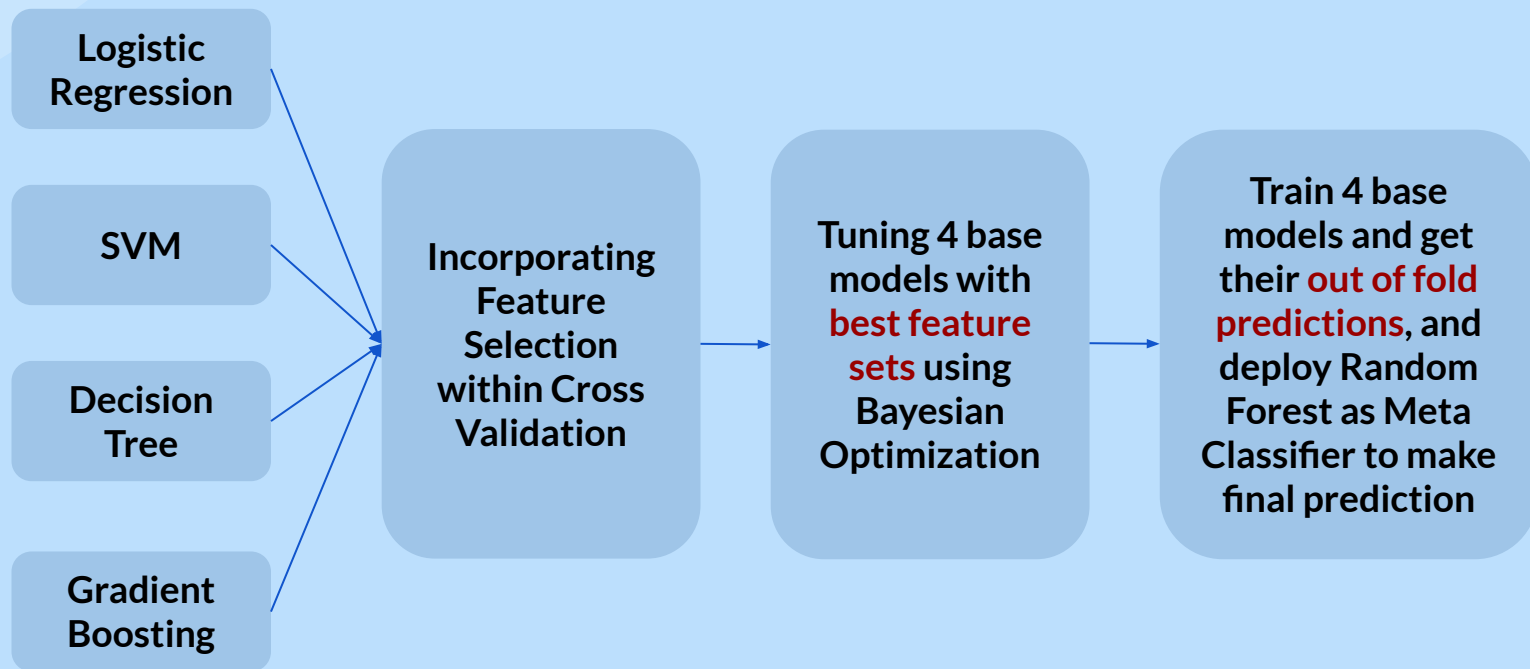
VS

LightGBM

XGBoost



# Stacking System Pipeline



**Average CV Training Accuracy: 0.906**



# Feature Selection for LightGBM

## Strategy:

Backward Stepwise Selection

**Best Train Accuracy Score:**  
**0.879**

## Numerical Features: 7

age, balance, duration,  
campaign, pcontact, previous,  
day\_of\_month

## Categorical Features: 29

### job:

job\_blue-collar,  
job\_entrepreneur,  
job\_housemaid,  
job\_management,  
job\_self-employed,  
job\_services,  
job\_student,  
job\_technician,  
job\_unemployed

### marital:

marital\_married,  
marital\_single

### education:

education\_secondary,  
education\_tertiary

### default:

default\_yes

### housing:

housing\_yes

### month:

month\_aug,  
month\_dec  
month\_feb,  
month\_jan,  
month\_jul,  
month\_jun,  
month\_mar,  
month\_may,  
month\_nov,  
month\_oct,  
month\_sep

### loan:

loan\_yes

### contact:

contact\_telephone

### poutcome:

poutcome\_success

# Feature Selection for XGBoost

## Strategy:

Backward Stepwise Selection

**Best Train Accuracy Score:**  
**0.890**

## Numerical Features: 6

age, balance, duration,  
campaign, pcontact,  
day\_of\_month

## Categorical Features: 28

### job:

job\_blue-collar,  
job\_entrepreneur,  
job\_housemaid,  
job\_management,  
job\_self-employed,  
job\_services,  
job\_student,  
job\_technician,  
job\_unemployed

### marital:

marital\_married,  
marital\_single

### education:

education\_secondary,  
education\_tertiary

### housing:

housing\_yes

### month:

month\_aug,  
month\_dec  
month\_feb,  
month\_jan,  
month\_jul,  
month\_jun,  
month\_mar,  
month\_may,  
month\_nov,  
month\_oct,  
month\_sep

### loan:

loan\_yes

### contact:

contact\_telephone

### poutcome:

poutcome\_success

# Hyper-parameter Tuning for LightGBM and XGBoost

## Strategy:

Bayesian Optimization

## Best Train Accuracy Score:

LightGBM: **0.934**; XGBoost: **0.931**

## LightGBM

num\_leaves: 104,  
learning\_rate: 0.14,  
max\_depth: 15,  
min\_child\_samples: 13,  
subsample: 0.58,  
colsample\_bytree: 0.39,  
reg\_alpha: 0.95, reg\_lambda: 0.55,  
min\_child\_weight: 5.30,  
feature\_fraction: 0.47,  
bagging\_fraction: 0.99, bagging\_freq: 6,  
max\_bin: 803, min\_data\_in\_leaf: 62

## XGBoost

learning\_rate: 0.20, max\_depth:  
10, min\_child\_weight: 7,  
subsample: 0.57,  
colsample\_bytree: 0.55,  
gamma: 0.69,  
reg\_alpha: 0.78,  
reg\_lambda: 0.31,  
num\_leaves: 56,  
min\_child\_samples: 16,  
feature\_fraction: 0.58,  
bagging\_fraction: 0.57,  
bagging\_freq: 2,  
max\_bin: 238,  
min\_data\_in\_leaf: 17



# Comparison of Three Classifiers

## Stacking

### Base models:

Gradient Boosting,  
Decision Tree,  
Logistic Regression,  
Support Vector Machine

### Meta model:

Random Forest

Train Accuracy: **0.906**



## LightGBM

Train Accuracy: **0.934**



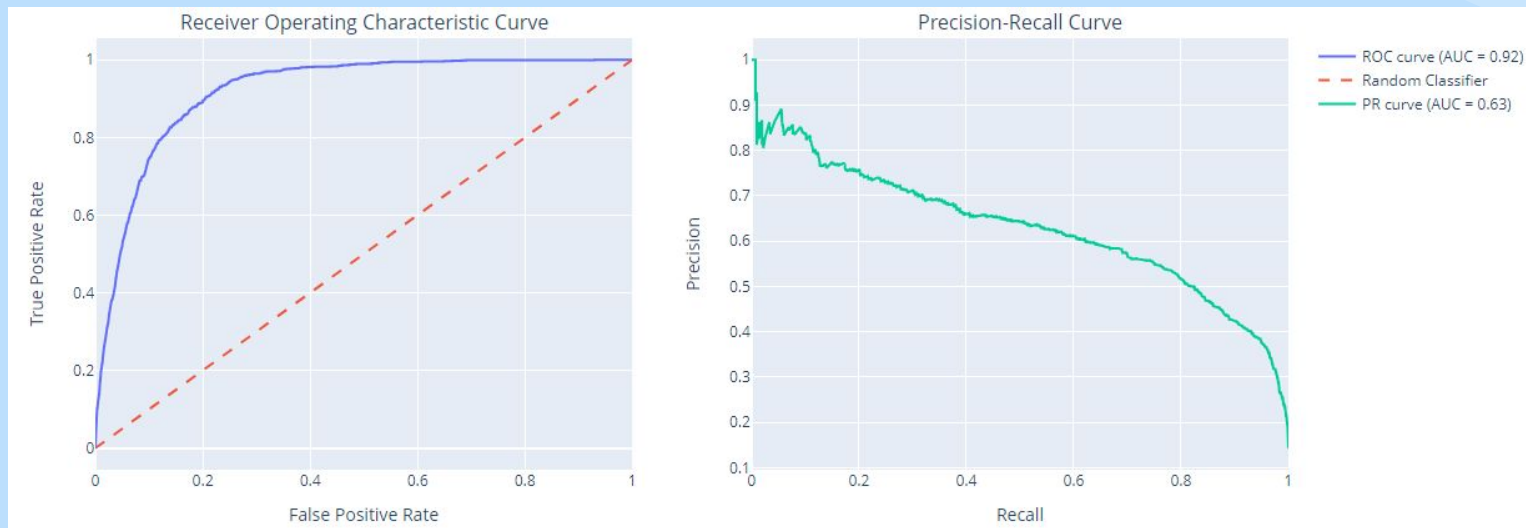
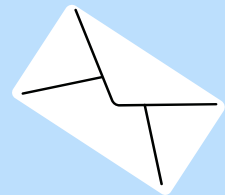
Test Accuracy: **0.888**

## XGBoost

Train Accuracy: **0.931**



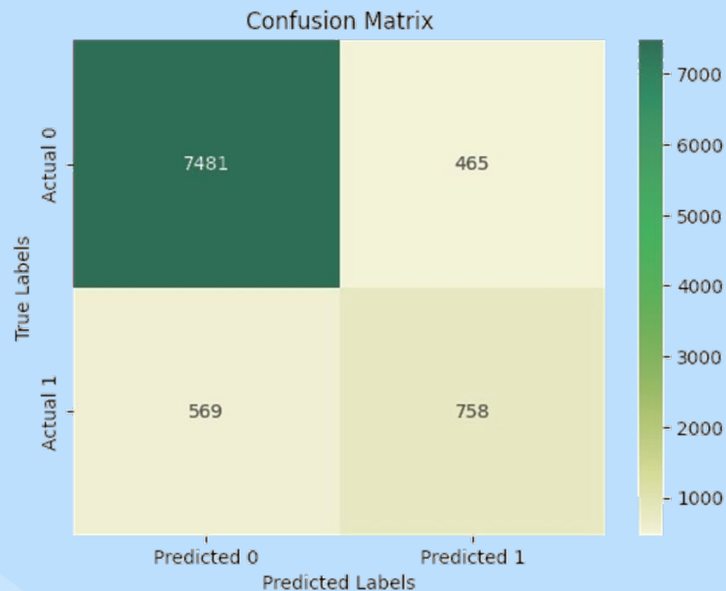
# Performance Summary



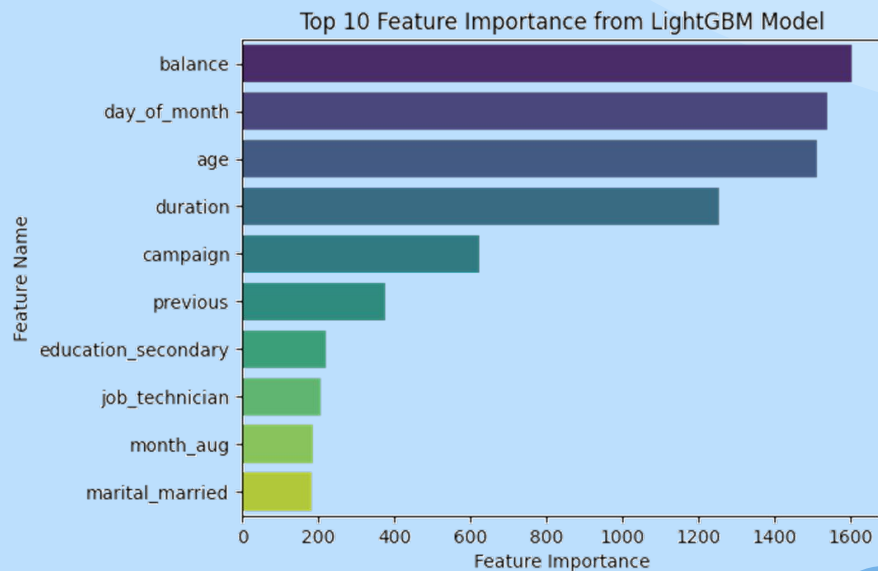
- The ROC curve leans towards the **upper-left corner**, and the **AUC** is close to 1.
- The Precision-Recall curve approaches the **upper-right corner**.



# Performance Summary



**True Positive: 758; True Negative: 7481;**  
**False Positive: 465; False Negative: 569**

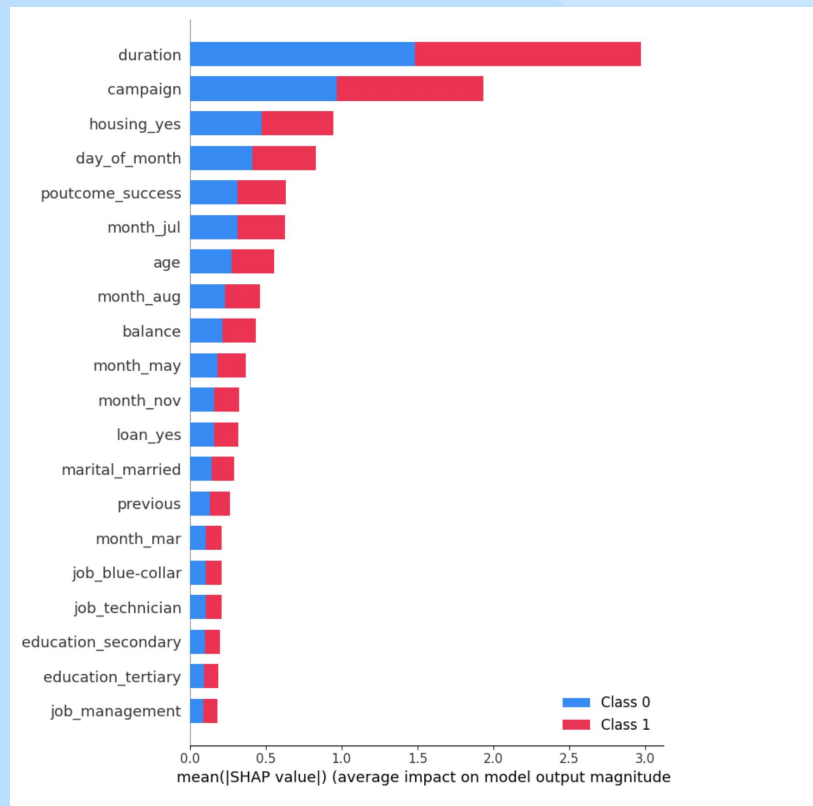
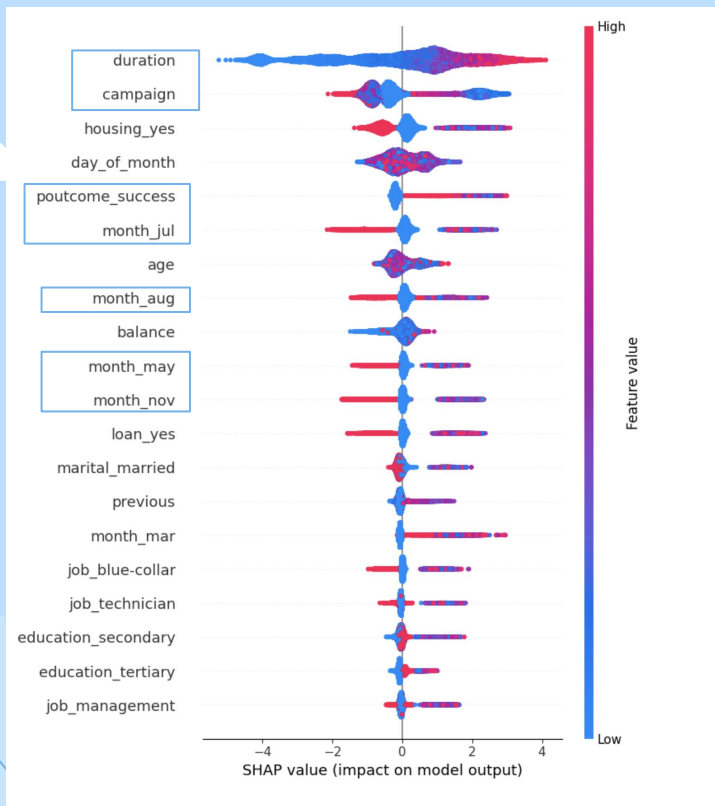


**Top 4 features: above 1200;**  
**Top 5-10 features: below 800**

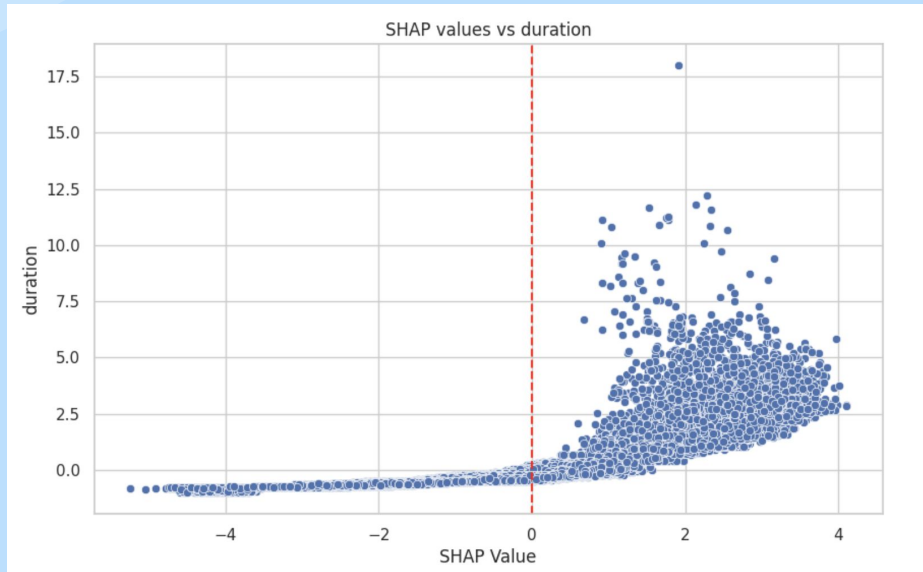
# 04. Business Insights & Conclusion



# SHAP Summary Plot

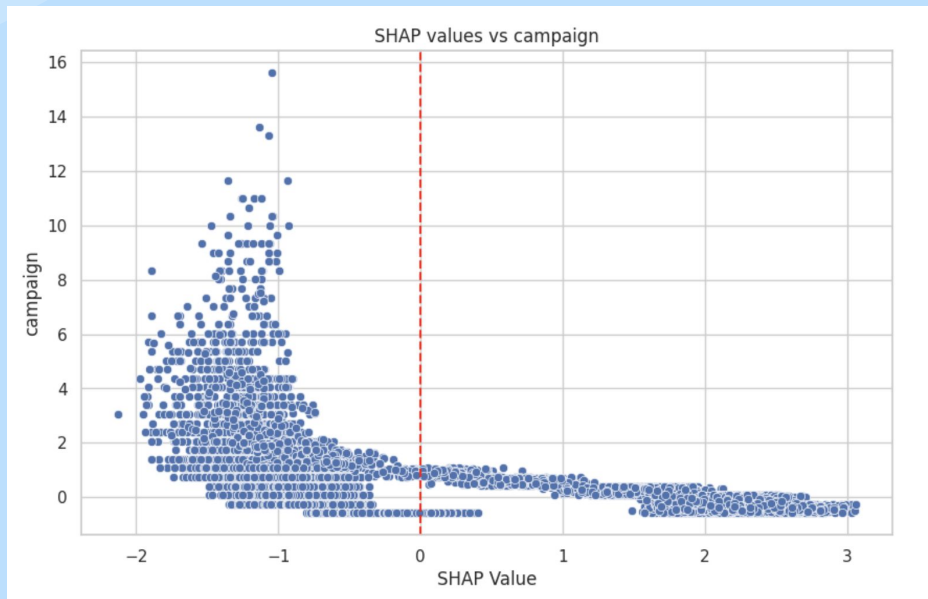


# SHAP Values vs Duration



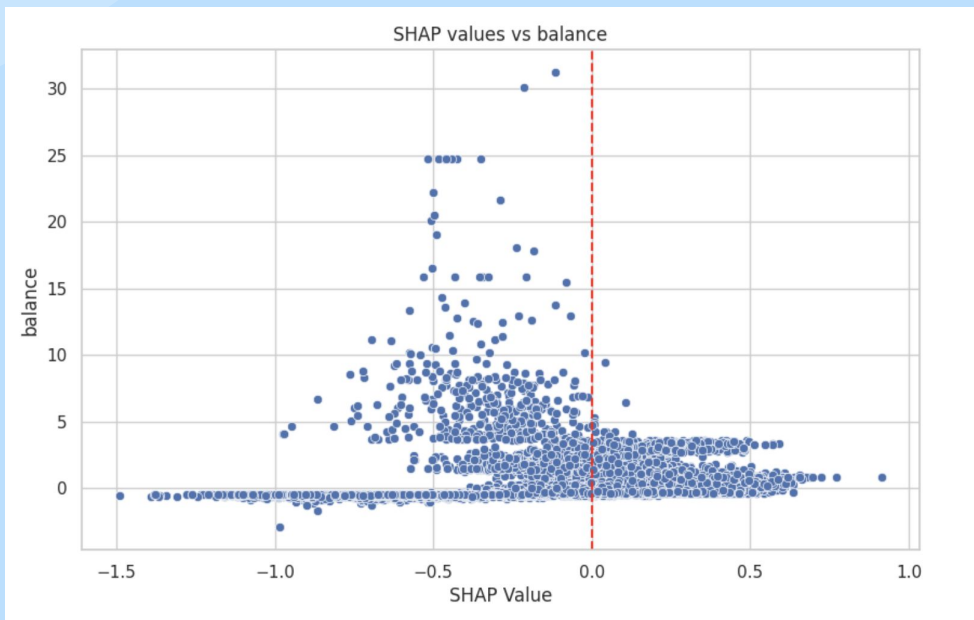
- High SHAP value
- Most impactful feature
- Duration > 0, positive impact on successful outcomes

# SHAP Values vs Campaign



- Number of contracts decreases the possibility of successful outcomes
- Focus more on quality rather than quantity


# SHAP Values vs Balance



- Lower balance: not clear in either direction
- Higher balance: impact on prediction becomes negative



# Thank You!



# Q&A

**Colab Link:** <https://drive.google.com/file/d/1BFzD6AI5aoldC99X-aGqR2nq7aXUbOpv/view?usp=sharing>