Modeling Next Product to Buy

Kowsalya Nitya Vootla

Business Problem: How can Pentathlon allocate customers to the most relevant department for promotional emails to drive profitability?

BACKGROUND

- *A 6-month test on email frequency showed that **two emails per week optimized engagement** and retention.*
- *Customers respond differently to promotions, but **no data-driven approach exists to match** them to the right department.*
- *Departments currently receive customer **email slots randomly**, creating inefficiencies.*

APPROACH

- *Analyze data from randomized email allocation experiment to identify **which department's emails each customer** is most likely to respond to.*
- *Use **Machine Learning Models** to generate **customized prediction for each customer.***
- *Implement a Smart Allocation Strategy where customers receive promotional **emails from departments** that **maximize their likelihood of purchase and profitability.***

Data on the LAST email sent to each customer
600k "Customer-promotional email" pairs

Demographics

- Cust ID
- Age
- Female
- Income
- Education
- Children

Department-specific customer purchase history

Freq_endurance, Freq_eater, Freq_team, Frew_strength, Freq_backcountry, Freq_racquet

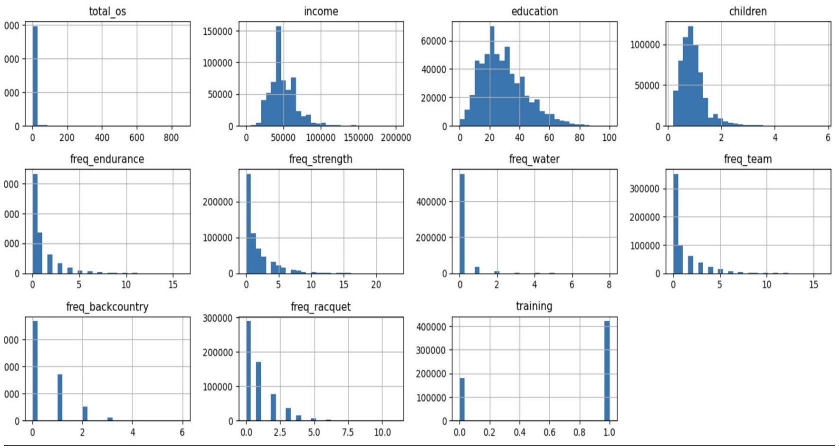
Outcome Variable

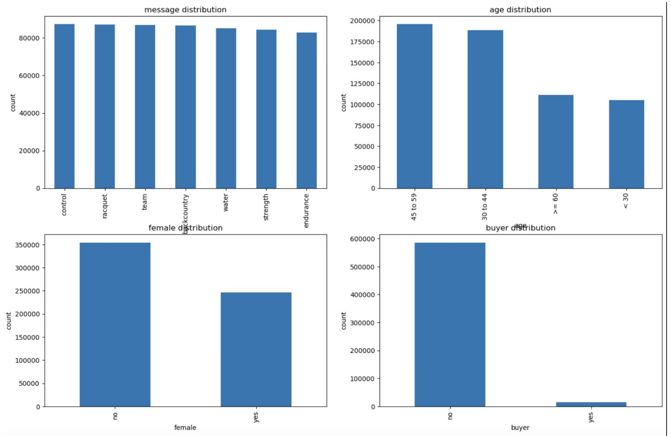
- Purchase in 2 days of email receipt (y/n)
- Total order Size (Euros)

Six message groups, one control group
Train:Test :: 70:30 split

Exploratory Data Analysis and Transformation

Data heavily imbalance and skewed towards non-buyers - ONLY 2.4% buyers



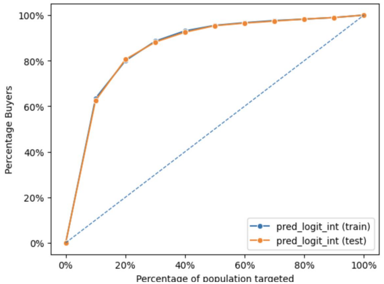
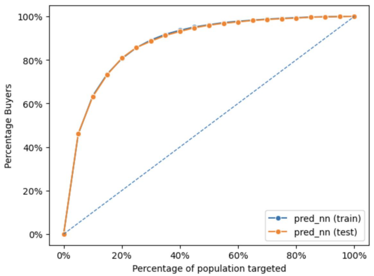
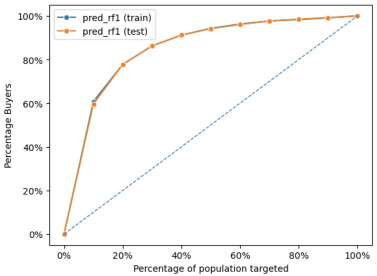
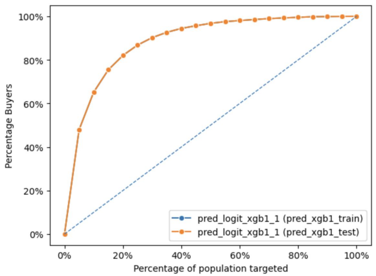


Income, children, education, total_os left skewed

Multiple Categorical variables (female, age, message)

Predicting Probability of Buying

- **Entire Train Dataset**
- **Rvar**: buyer = yes
- **Evar**: 'income', 'education', 'children', 'freq_endurance', 'freq_strength', 'freq_water', 'freq_team', 'freq_backcountry', 'freq_racquet','message_control', 'message_endurance', 'message_racquet', 'message_strength','message_team', 'message_water', 'female', 'age_30_44, 'age_45_59', 'age_60a'
- **Exclude total_os from evar**

Logistic Regression	Neural Network	Random Forest	XGBoost
Log transform	Scaled df	One-hot encode + convert to binary	One-hot encode + convert to binary
Int terms added: message: (all other variables)	Hls = (3,3), Apha = 0.1	Max_features = 6, max_samples = 0.5	Max_depth = 5, n_estimators = 51
			
AUC: 0.884	AUC: 0.891	AUC: 0.871	AUC: 0.899

% of customers for whom the message maximizes probability of purchase

Utilizing the predicted probability of purchase to determine the best message per customer:

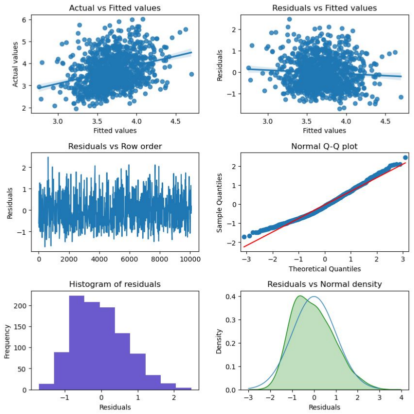
Message Type	Logistic Regression	Neural Network	Random Forest	XGBoost
Endurance	73.20%	45.34%	87.86%	52.62%
Strength	19.39%	30.49%	2.34%	23.65%
Racquet	4.57%	0.52%	0.15%	6.26%
Water	1.07%	0.17%	5.96%	1.92%
Team	1.05%	23.48%	2.75%	1.78%
Backcountry	0.72%	0.00%	0.002%	7.64%
No message	~0.00%	0.00%	0.912%	6.12%

Predicting Total Order Size

- **Train Dataset, filter on buyer == ‘yes’**
- **Rvar**: total_os
- **Evar**: 'income', 'education', 'children', 'freq_endurance', 'freq_strength', 'freq_water', 'freq_team', 'freq_backcountry', 'freq_racquet','message_control', 'message_endurance', 'message_racquet', 'message_strength','message_team', 'message_water', 'female', 'age_30_44, 'age_45_59', 'age_60a'

Linear Regression

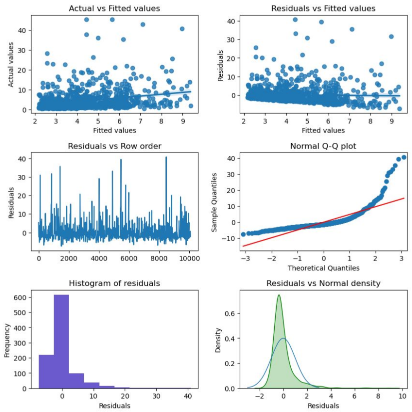
Int terms added: message: (all other variables)



Baseline	
R^2: 0.000	R^2: 0.118
MAE: 0.653	MAE: 0.611
MSE: 0.649	MSE: 0.573

Neural Network

Hls= (3,) , Alpha = 0.1



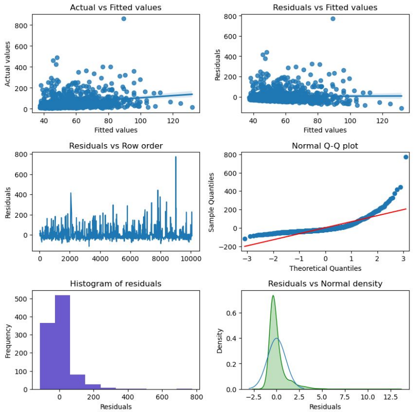
Baseline	
R^2: -0.000	R^2: 0.065
MAE: 3.03	MAE: 0.2881
MSE:22.66	MSE: 21.197

R^2 improves, MAE and MSE decreases compared to baseline. However, R^2 are still very low.

Predicting Total Order Size

Random Forest

Max_features = 6 , max_samples = 0.7

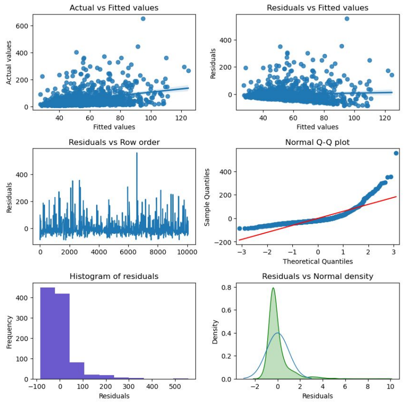


Baseline

Baseline	Random Forest
R^2: -0.0001	R^2: 0.703
MAE: 39.531	MAE: 37.668
MSE:3859.43	MSE: 3587.72

XGBoost

Learning_rate = 0.2 , max_depth = 1



Baseline

Baseline	XGBoost
R^2: -0.0001	R^2: 0.0744
MAE: 39.53	MAE: 37.48
MSE: 3859.43	MSE: 3572.61

R^2 improves, MAE and MSE decreases compared to baseline. However, R^2 are still very low and residual plots are suboptimal with visible heteroscedasticity.

Decision (approach to calculating order size)

Utilize Average order size for each message type from historical buyer data

% of customers for whom the message maximizes expected profit

Expected Profit = probability of purchase * average order size * (1-COGS)
COGS = 60%

Message Type	Logistic Regression	Neural Network	Random Forest	XGBoost
Endurance	56.47%	33.49%	0%	37.79%
Strength	12.5%	4.56%	0%	17.28%
Racquet	17.48%	2.18%	0%	13.1%
Water	6.43%	0.17%	100%	17.61%
Team	3.44%	34.40%	0%	3.3%
Backcountry	0.72%	~0.00%	0%	8.57%
No message	~0.00%	0.00%	0%	2.35%

Expected profit on average (Euros) is highest for customized messages

	Logistic Regression	Neural Network	Random Forest	XGBoost
Customized message	0.68	0.65	0.61	0.70
Randomised message	0.55	0.55	0.55	0.55
Same message				
Endurance	0.598	0.604	0.518	0.603
Strength	0.576	0.583	0.525	0.581
Racquet	0.568	0.584	0.589	0.583
Water	0.618	0.639	0.610	0.627
Team	0.574	0.598	0.580	0.585
Backcountry	0.545	0.570	0.570	0.569
No message	0.426	0.447	0.482	0.447

Extrapolated profits to 5M customers & Improvement metrics

Extrapolated profit when…	Logistic Regression	Neural Network	Random Forest	XGBoost
Personalized message is sent	€3,394,907.78	€3,267,902.93	€3,051,997.78	€3,486,245.57
Improvement in profit (%) when **personalized message** is sent against				
Same message	9.81%	2.33%	0%	11.14%
Random message	23.03%	18.42%	10.60%	26.34%
No message	59.43%	46.31%	26.70%	56.00%

- **Personalized messaging seems to be the best approach**
- **XGBoost delivers the highest % improvement in profit compared to same/random/no message**

Evaluating and Improving the New E-mail Policy Proposal

STRENGTHS

✔ ***Data-Driven Decision Making*** – Allocates promotional emails based on expected profitability

✔ ***Fair Departmental Distribution*** – Split emails between the top two high-profit messages.

✔ ***Continuous Learning*** – Monthly re-evaluation refines predictions using recent data.

WEAKNESS

❌ ***Bias Toward High-Performing Messages & Customer fatigue***– Other messages may never be tested.

❌ ***Short-Term Profit Focus*** – May lead to aggressive marketing strategies that hurt long-term engagement.

❌ ***No Built-in Experimentation*** – Lacks A/B testing to improve predictions and customer response modeling.

IMPROVEMENTS

🔹 ***Introduce A/B Testing*** – Randomly assign some customers a different message type to explore effectiveness.

🔹 ***Control for Confounding Factors*** – Consider seasonality, self-selection bias, and prior purchases.

🔹 ***Implement Uplift Modeling*** – Measure impact by comparing P(Purchase | Message) - P(Purchase | No Message) in randomized trials.


THANK
YOU