Gourmet Haven - Maximizing Marketing Outcomes with Data

Lisa Shoff, Sibani Mohapatra, Amna Tariq
2.6.25

Gourmet Haven - Maximizing Marketing Outcomes with Data

Challenge:

Refine the marketing strategies to enhance the effectiveness of marketing campaigns.

Gourmet Haven - About the Data

Demographic Info

Year of Birth, Education, Marital Status, Income, Teens in Home, Kids in Home

Brand Relationship

Days Since Last Purchase (Recency)
Date Customer Enrolled
Accepted Previous Campaigns
Complaints

Purchase Info

Amount Spent in Categories
Web vs In-Store

Gourmet Haven - About the Model

What characteristics make a person more likely to respond to your marketing campaign?

Purchase Info?

Brand Relationship?

Demographic Info?

Gourmet Haven - Key Findings

The Most Predictive Findings:

Date Enrolled:

Customers who have been members for **LONGER** are more likely to respond.

Days Since Last Purchase:

Customers who have shopped within the

past 25 days are more likely to respond.

Previous Campaign:

Customers who have responded to **ANY** of the previous campaigns are most likely to respond.

Brand Relationship

Gourmet Haven - Recommendation

Brand Loyalty Program - “Gourmet Insider”

- Built on the idea that the brand relationship is the strongest driver of marketing success
- Customized focus bases on specific drivers of marketing acceptance
- Enhanced content recommendations based on additional findings to maximize success.

Gourmet Haven - Recommendation

Program Features Based on Findings:

Date Enrolled:

Customers who have been members for **LONGER** are more likely to respond.

Focus on established members vs. bringing in new member

Days Since Last Purchase:

Customers who have shopped within the **past 25 days** are more likely to respond.

Engage with the members at least every 25 days.

Previous Campaign:

Customers who have responded to **ANY** of the previous campaigns are most likely to respond.

Target customers who previously accepted a marketing campaign

Gourmet Haven - Recommendation

Loyalty Program - Additional Finding Driven Recommendations

Finding: Amount Spent on Meat is a strong predictor and we know that “Gold Shoppers’ are more likely to respond to marketing-

Hi! This month at Gourmet Haven, if you spend $30 on meat you get a free “Gold” upgrade.

Gourmet Haven - Recommendation

Recommended Features -

- Finding: In-store shoppers are less likely to respond to the marketing efforts, and online shoppers are more likely. We recommend continuing to incentivize online purchases.
  - **This week only, get an extra 15% off online purchases only**.
- Finding: Single customers are more likely to respond
  - **Galentine's day! Bring your girl group for a free wine tasting and a 10% off wine coupon.**

Recommend continuing to assess and improve future recommendations from the model learnings.

Gourmet Haven - Summary

Brand Relationship

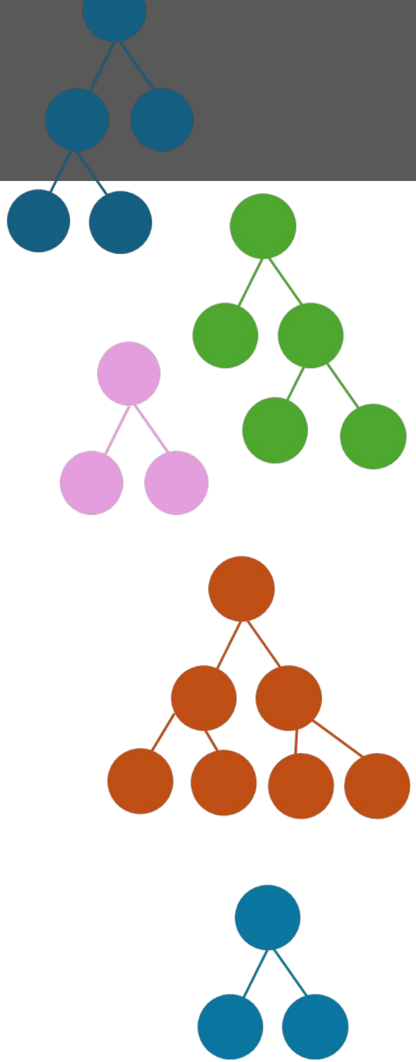
The Brand Relationship is the strongest driver of marketing success

A loyalty program that engages long-term customers at least every 25 days will maximize marketing campaign acceptance.

Using additional insights for specific marketing ideas will further increase likely of campaign success

TECHNICAL PRESENTATION

About the model - XGBoost



Multiple **Shallow** trees build sequentially

New trees built based on the errors of the previous tree

Learning Rate slows down the progression, taking small steps in the right direction

AUC Score - How do we know our model is “good”?

AUC Score:

Helps us understand the model’s ability take the information it has learned and then predict future actions based on past learnings.

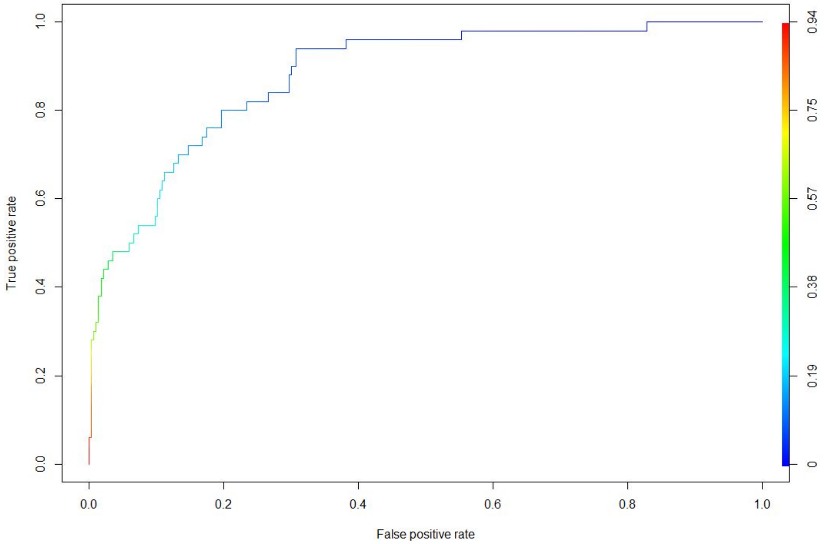
ROC Curve (Receiver Operating Characteristic):

A graph showing the trade-off between the True Positive Rate (sensitivity) and the False Positive Rate (1-specificity) at different classification thresholds.

What’s a good score?

A 0.5 AUC represents “random guessing”, so anything higher means that our learned about meaningful relationships in the data that it can use to increase our prediction accuracy.

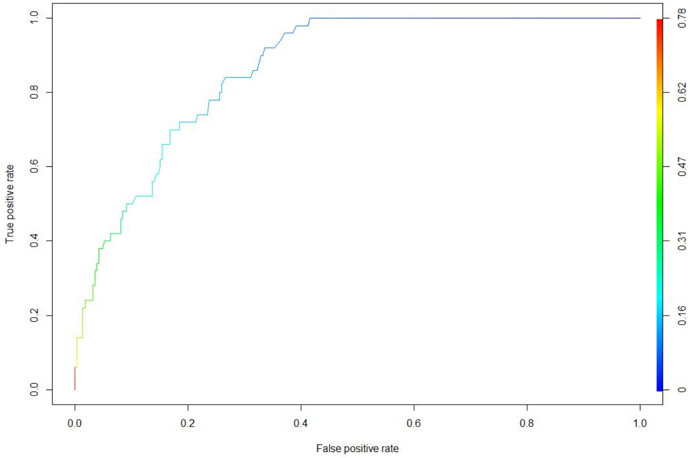
XGBoost
AUC = 0.8809091



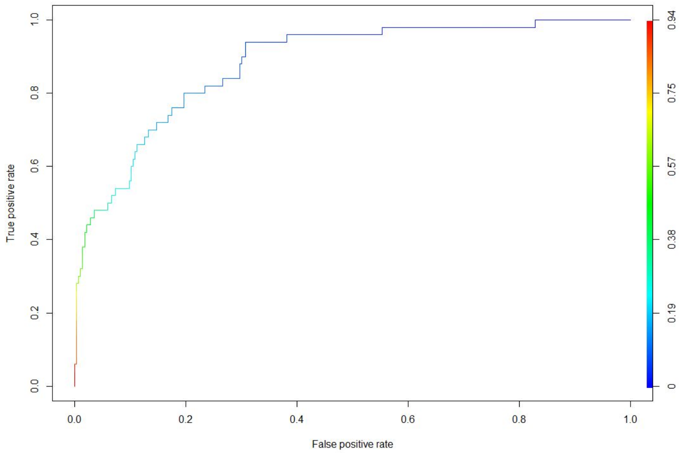
Model Choice - XGBoost chosen due to better AUC Performance

Tree Based Ensemble Methods

Random Forest
AUC = 0.8654545



XGBoost
AUC = 0.8809091



Model Choice - Generalizing Approach

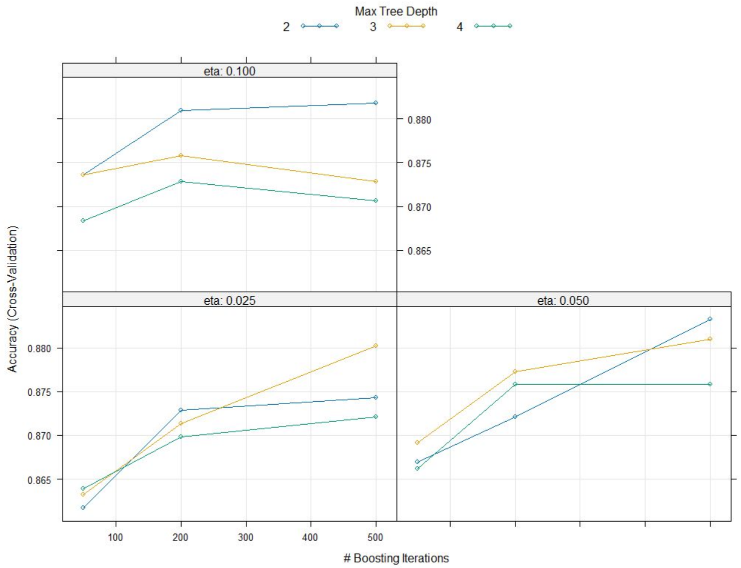
Training and Testing - 80/20

Model Choice - Generalizing Approach

Tuning Parameter 5 Fold Cross Validation:

Optimizing the parameters will help prevent overfitting.
Low Max Depth - prevents overly complicated trees = overfitting
Low eta - Slower learning = better learning

Cross Validation of Tuning Parameters ensure that the chosen parameters are best for unseen data, and not just training data.



Model Choice - Generalizing Approach

```
tuneGrid = expand.grid(
            nrounds = c(50,200, 500),
            eta = c(0.025, 0.05, .1),
            max_depth = c(2,3,4),
            gamma = 0,
            colsample_bytree = 1,
            min_child_weight = 1,
            subsample = 1)
```

- Added increased option for Nrounds to prevent overfitting
- Added a larger ETA to test
- Added a larger Max Depth to allow for more expressive trees (careful with overfitting here)

```
model_gbm$bestTune
 nrounds max_depth  eta gamma colsample_bytree min_child_weight subsample
     500         2 0.05     0                1                1         1
```

Model Choice - Bias & Variance

XGBoost and Bias:

The sequential nature of the tree building, correcting the errors or the previous tree, allows for excellent error correction, making a very good fit to training data and low bias.

Model Choice - Bias & Variance

XGBoost and Variance:

1) Ensemble methods, like XGboost, use multiple trees to reduce variance by preventing the overfitting risk of a single tree.
2) Boosting approach learns slowly - takes small steps in the right direction because of the learning rate- leading to better predictions
3) Focusing on the residuals allow the model to improve the fit where it does not perform well

Gourmet Haven - Feature Engineering

Demographic Info

Year of Birth, Education, Marital Status, Income, Teens in Home, Kids in Home

Brand Relationship

Days Since Last Purchase (Recency)
Date Customer Enrolled
Accepted Any Previous Campaigns
Complaints

Purchase Info

Amount Spent in Categories
Web vs In-Store

Gourmet Haven - Feature Engineering

Focus on Brand Relationship

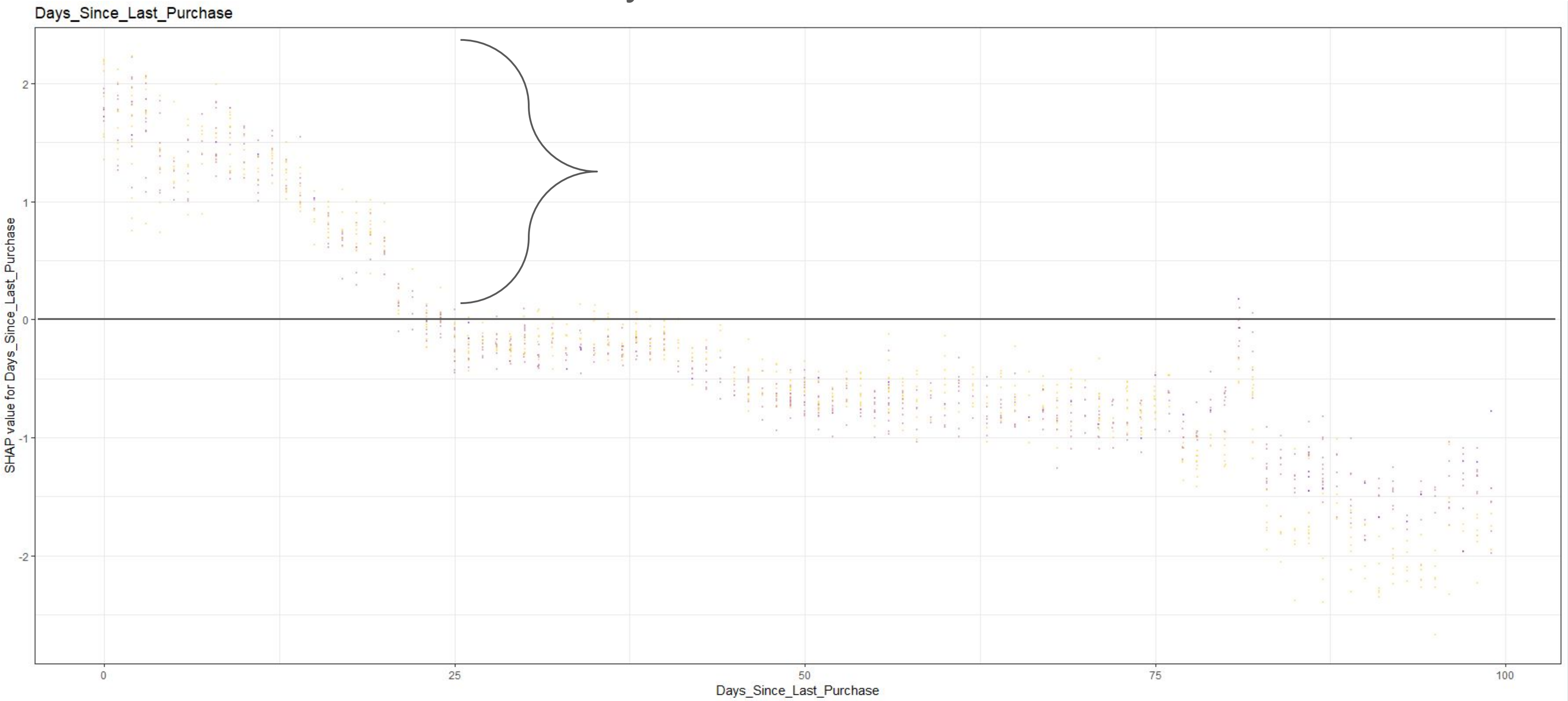
Date Enrolled: *Weeks Enrolled, Months Enrolled*

Days Since Last Purchase - *Bucketed into 25 day buckets (4 buckets)*

Any Past Campaign Accepted - *If any of the 5 previous campaigns had been accepted*

Model Choice - Feature Engineering

"Days Since Last Purchase"



Model Choice - Feature Engineering

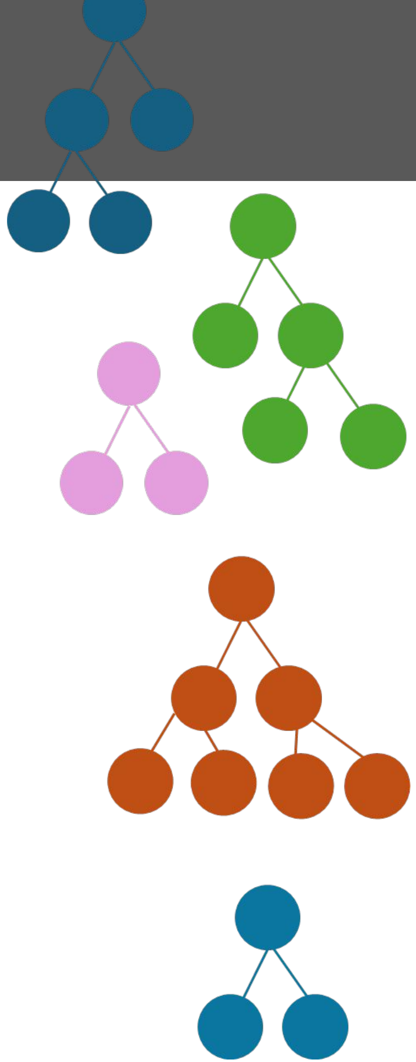
Binning “Days Since Last Purchase” into Buckets of 25 days

Bucket #1	Bucket #2	Bucket #3	Bucket #4
1-25 days	26-50 days	51-75 days	76-99 days

Gourmet Haven - Feature Engineering

Top 3 Shap Values:
Days Since Last Purchased - Bucket 1 (0-25 days
Time Since Enrollment
Any Campaign Accepted

Summary



XGBoost Model chosen for inherent benefits and superior performance.

Model Generalization and Bias/Variance Balance was Prioritized

Recommendations are driven by highest predicting variables.