What Drives Customer Engagement

Understanding What Makes Customers Say Yes!

Gourmet Haven Case

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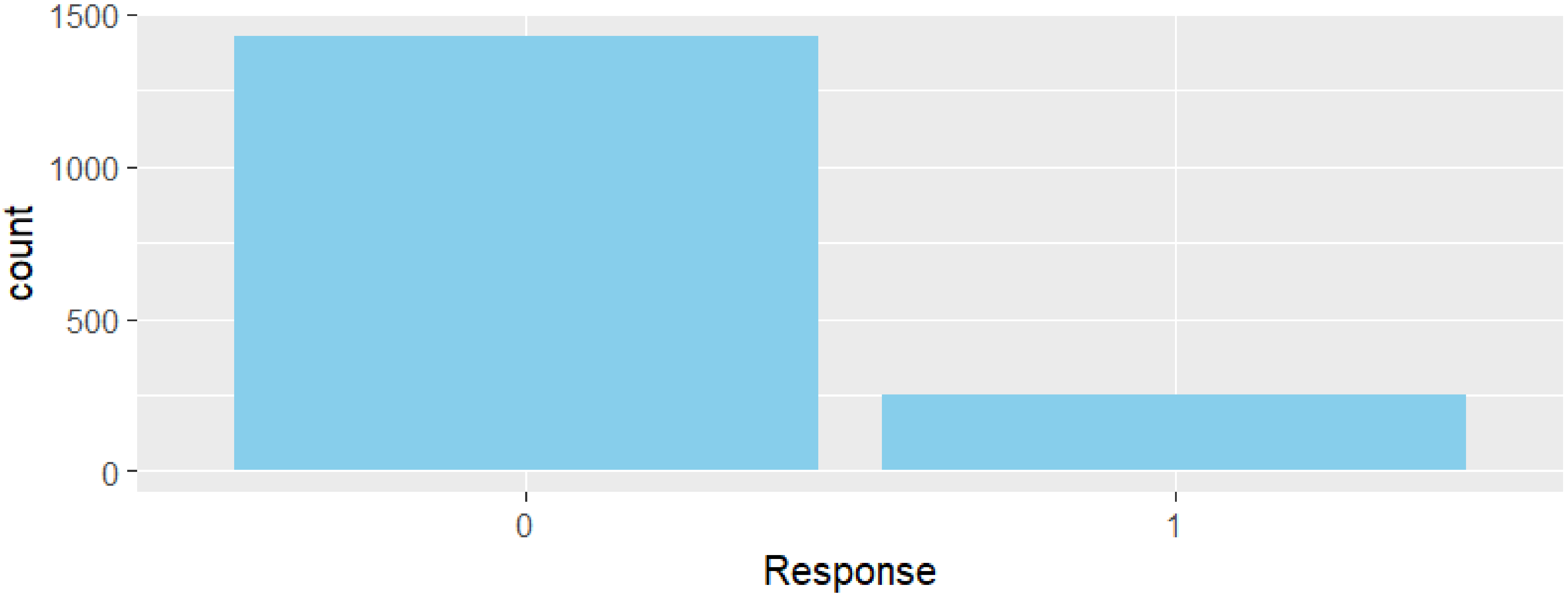
Business Challenge

Gourmet Haven seeks to refine the effectiveness of its marketing campaign strategies.

Specifically seeking to **maximize profit** for their next direct marketing campaign by having a better understanding of customer characteristics whilst optimizing target strategies plus enhanced campaign performance.

Count of Response



BIG QUESTION

- Why do some customers accept marketing campaigns while others don’t?
- Our analysis explores key customer behaviors that explains customer-to-business interaction.

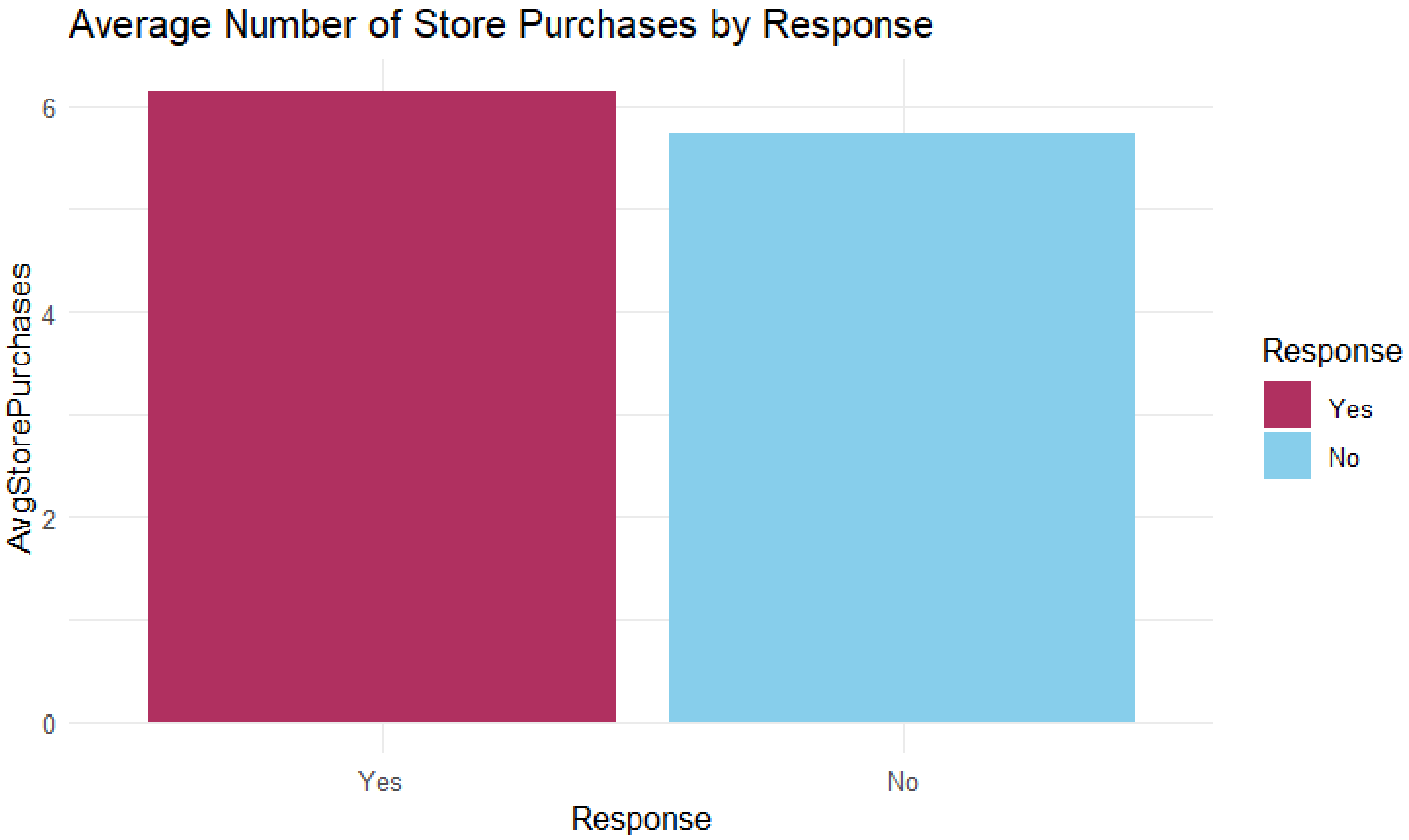
The Top Factors That Influence Acceptance

- Recent Purchases
- Past Campaign Engagement
- Marital Status
- Year of Enrollment
- Spending Habits
- Education Level
- Web Visits
- Family Structure

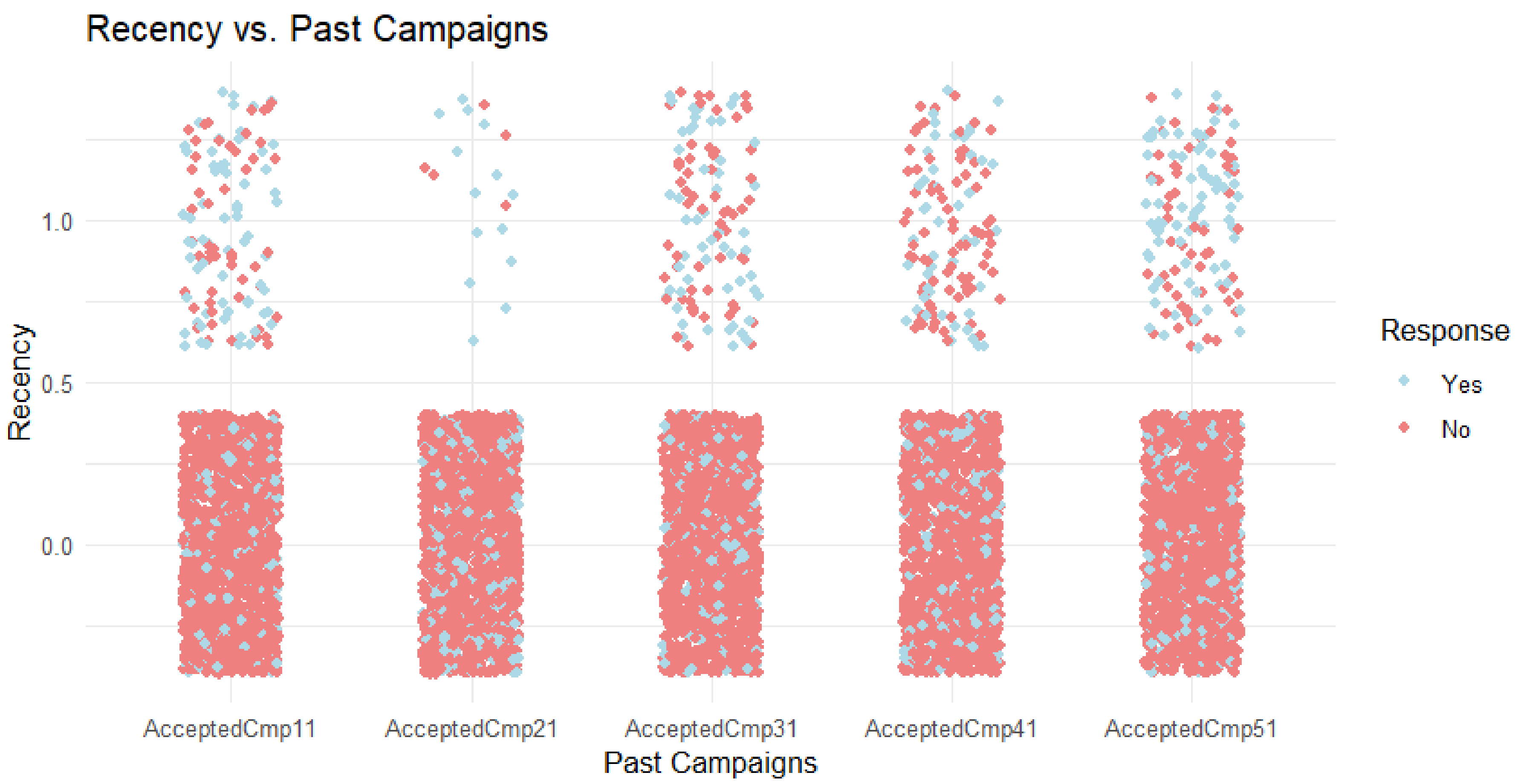
Insights on Customer Behavior

- **Recent purchases** leads to High engagement.
- **Past campaign participants** might have lower interest.
- **Single customers** engage less than married ones.
- **Customers with teenagers** respond well to campaigns.

Average Number of Store Purchases based on Response

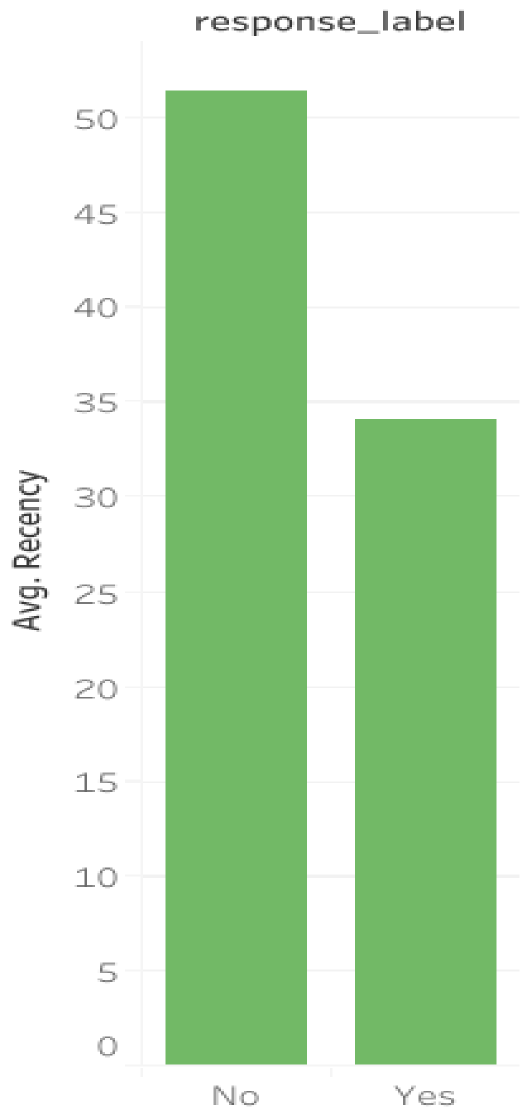


Interaction Between Recency and Past Campaigns



Response Based on RECENT Purchases

- Those who accepted the campaign were customers who made recent purchase



Recommendations for Future Campaigns

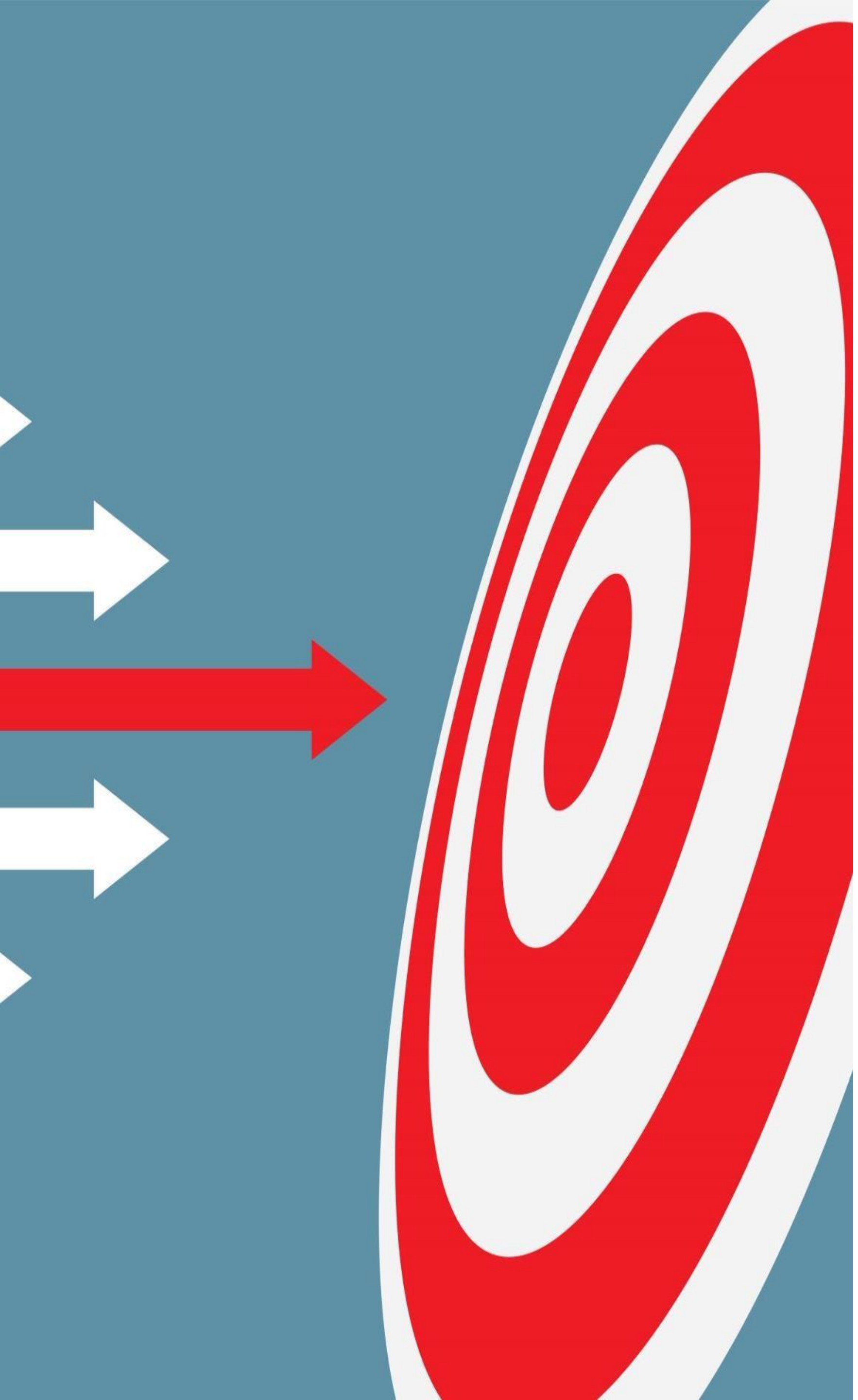
- **Better Targeting:** Identifies key customer segments likely to accept campaigns.

- **Cost Reduction:** Avoids wasted marketing efforts on unresponsive groups.

- **Personalized Strategies:** Based on customer engagement patterns and demographics.

Actionable Insights:

- **Target recent buyers** for higher acceptance rates.
- Avoid over-marketing to previous campaign participants.
- Focus on **families with teenagers** for higher engagement.



GOAL

- **Objective:** To develop a model that helps **Gourmet** identify effective campaign strategies to increase customer responses.

FEATURE ENGINEERING

- Converted DT_Customer to date
- Extracted year and month from date
- Collapse marital status into two categories (single and married)

Model Choice

CHOSEN MODEL: LOGISTIC REGRESSION (BINARY CLASSIFICATION)

FEATURE SELECTION APPROACH: FORWARD SELECTION (AIC-BASED STEPWISE SELECTION)

Logistic Regression Mechanics

Our response variable is binary, we used logistic regression, which predicts **probabilities** rather than direct outcomes.

The model uses the **logit function** to convert predictions into values between 0 and 1.

Evaluation Metric

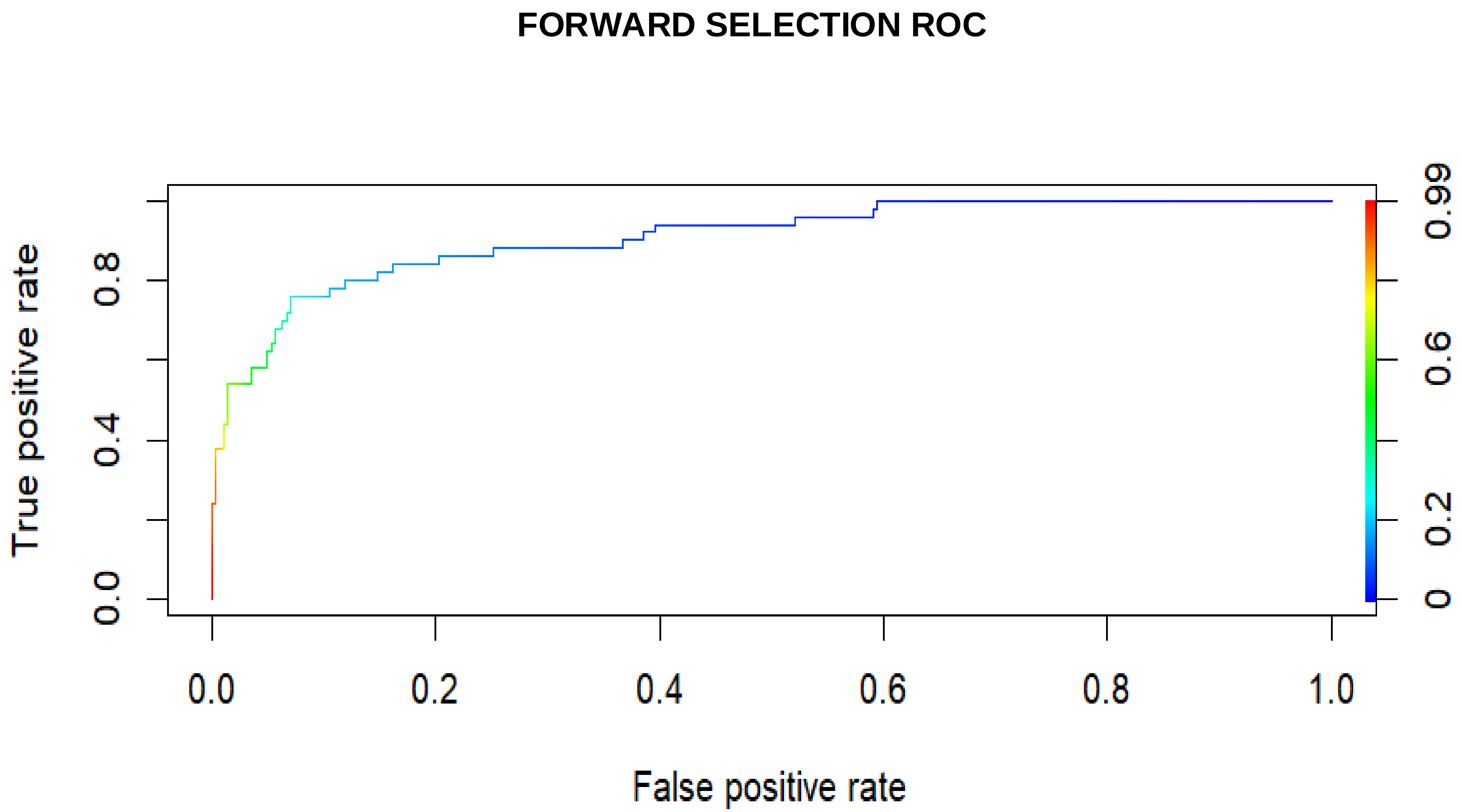
- **Classification Metric Used:**
  - AUC
- **Key Metrics from the Models:**

✓ **Random Forest :** AUC = 0.869

✓ **XGBoost :** AUC = 0.893

✓ **Logistic Regression(LASSO):** AUC=0.903

✓ **Logistic Regression (Forward subset selection):** AUC : 0.909


FORWARD SELECTION ROC
True positive rate
False positive rate
0.0
0.2
0.4
0.6
0.8
1.0
0.99
0

COEFFICIENTS OF PREDICTORS

Predictor	Coefficient
(Intercept)	-1924.71
AcceptedCmp51	-1.685
Recency	0.0312
AcceptedCmp31	-1.857
Dt_Cus_Year	0.9573
AcceptedCmp11	-1.719
Marital_Statussingle	-1.173
MntMeatProducts	-0.00187
NumWebVisitsMonth	-0.1202
AcceptedCmp41	-1.151
NumStorePurchases	0.199
NumWebPurchases	-0.154
Teenhome	0.7401
EducationPhD	-0.7145
EducationBasic	1.7764
EducationMaster	-0.5434
MntFruits	-0.00456

Generalization Approach

- Data partitioning
- Cross-validation (5-fold)
- Feature Selection

Bias-Variance Tradeoff

- **High Bias (Underfitting) :** Avoided by iteratively adding key predictors.
- **High Variance (Overfitting):** Controlled via feature selection and K Fold Cross Validation.
- **Steps Taken to Balance Tradeoff:**
  - Retained only statistically significant features and cross-validation to prevent overfitting.
  - Performance validated using **ROC-AUC**.

THANK YOU