

A2 Assignment

HOUSEHOLD SPENDING TREND ANALYSIS AT BBY INSIGHTS AND PREDICTIVE MODELING

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The importance of understanding customer spending patterns

BBY offers a membership and loyalty program designed to give customers easy access to great benefits and discounts through email, and physical direct mail coupons tailored to the household shopping habits

Maximizing our customer's revenue potential by offering relevant promotions is important to the company's success,

We want to build accurate predictive models to modeled household revenue from a predefined household data set of our loyalty customers.



DATA OVERVIEW

Description of the data sets used and preparation

Loyalty Customer Data sets

- 1. Membership Data
- 2. Consumer Purchasing Habits
- 3. Household Donation History
- 4. Household Magazine Subscription history
- 5. Household Political Leanings

Pre-processing Rationale

Handling Missing values

Relevance of variables

Outliers

15,000
TRAINING SET OBSERVATIONS

5,000
TESTING SET OBSERVATIONS

~6,000

TESTING SET OBSERVATIONS

80 VARIABLES

THE PROCESS



Peature Selection

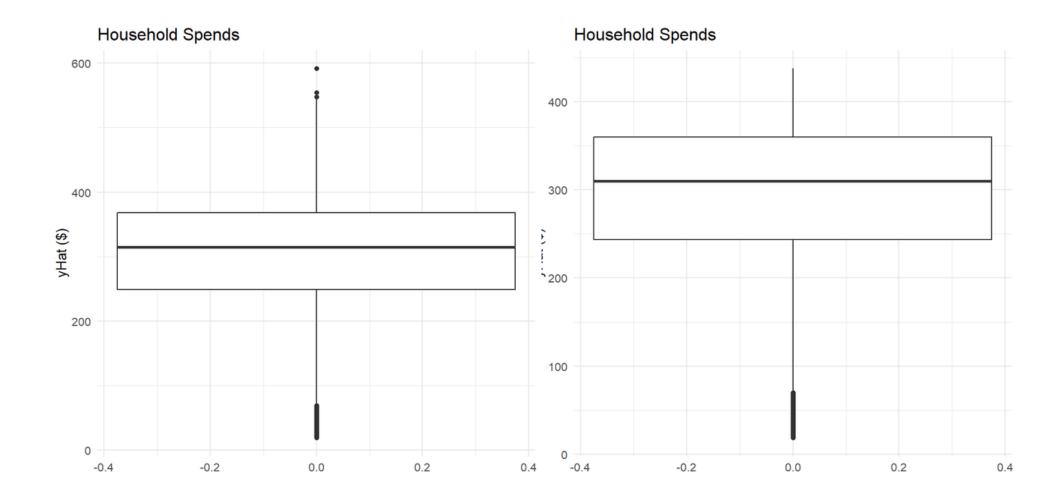


EXPLORATORY ANALYSIS (EDA)

Key highlights from EDA

Understanding the data

1. Outlier Detection

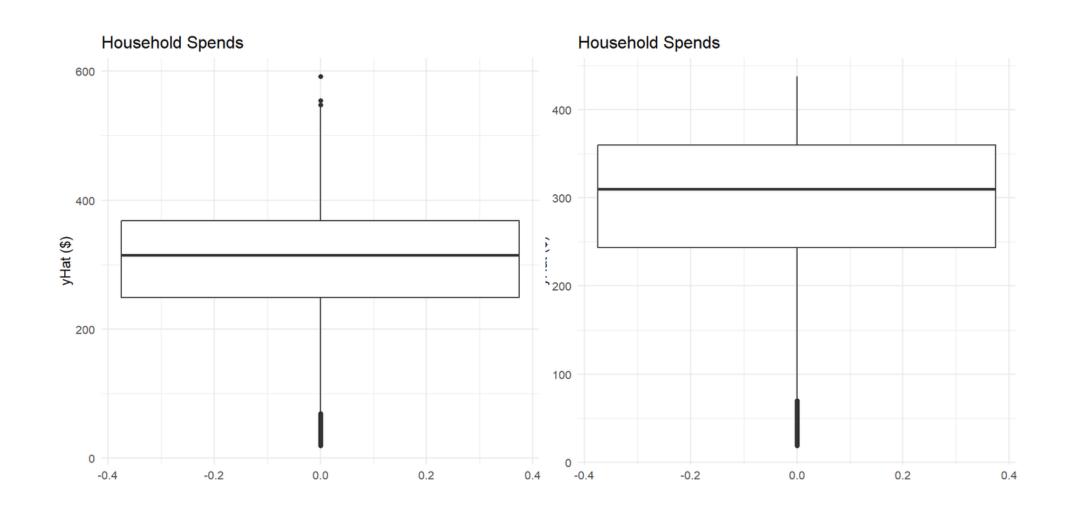


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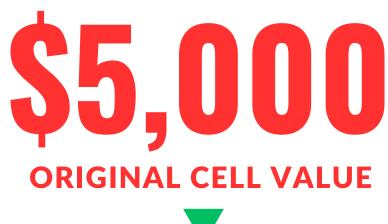
Understanding the data

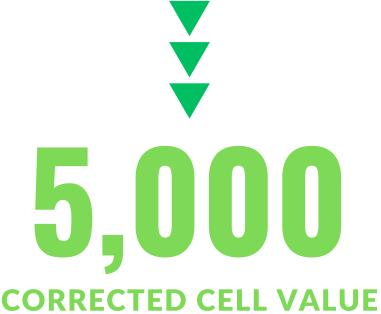
1. Outlier Detection



2. Numerical vs Categorical Variables

`EstHomeValue` & `LandValue`





EXPLORATORY ANALYSIS (EDA)

Key highlights from EDA

Understanding the data

- 1. Outlier Detection
- 2. Numerical vs Categorical Variables
- 3. Summarizing the Data

11
NUMERICAL VARIABLES

69
CATEGORICAL VARIABLES

14,250
OBSERVATIONS

FEATURE SELECTION

Designing the data for predictive modeling

Addressing variables that were excluded from our analysis.

Set Criteria:

- 1. Atleast 50% of values must not be missing
- 2. Check for relevance of the features
 - a. Uniqueness (`TmpID`)
 - b. Value Add (`Veteran`)
 - c. Ethical Concerns (`EthnicDescription`)

NUMERICAL VARIABLES

12
CATEGORICAL VARIABLES

14,250
OBSERVATIONS

MODEL SELECTION

Overview of the modeling methods employed

Linear regression, Decision tree, Random forest, XGBoost

Linear Regression

A fundamental statistical and machine learning technique where the goal is to model the relationship between a dependent variable (yHat) and explanatory variables independent variables.

We explore Linear
Regression with all variables
as well as the Parsimonious
version

Decision Tree

A flowchart-like tree structure where an internal node represents a feature(or attribute), the branch represents a decision rule, and each leaf node represents the outcome.

Prone to overfitting and often used as a baseline model.

Random Forest

Primarily used for classification and regression. It operates by constructing multiple decision trees during training and outputting the class that is the mean prediction of the individual trees. Random forests correct for decision trees' habit of overfitting to their training set.

XG Boost

is an advanced implementation of gradient boosting algorithm. It's a scalable and accurate implementation of gradient boosting machines, designed to be highly efficient, flexible, and portable

Fitting the first Linear Model

8.7%

R - squared

\$89.4 \$88.5

RMSE (train) RMSE (valid.)

48.6% 45.8%

MAPE (train) MAPE (valid.)

Fitting the first Linear Model

Fitting the Parsimony Model

8.7%

R - squared

\$89.4 \$88.5

RMSE (train) RMSE (valid.)

48.6% 45.8%

MAPE (train) MAPE (valid.)

1.2%

R - squared

\$93.2 \$91.9

RMSE (train) RMSE (valid.)

50.9% 47.8%

MAPE (train) MAPE (valid.)

Model Summary

Original Linear Model

8.7%



R - squared

\$89.4

RMSE (train)

48.6% 45.8%

MAPE (train)

MAPE (valid.)

\$88.5

RMSE (valid.)

Parsimony Model

R - squared

\$93.2 \$91.9

RMSE (train)

RMSE (valid.)

50.9% 47.8%

MAPE (train)

MAPE (valid.)

Broadening the parameters

- More lenient constraint
- No outlier detection
- Basic data cleaning only

Original Model Summary

Original Linear Model

8.7%

R - squared

\$89.4 \$88.5

RMSE (train)

48.6% 45.8%

MAPE (train)

MAPE (valid.)

RMSE (valid.)

Parsimony Model

R - squared

\$93.2 \$91.9

RMSE (valid.) RMSE (train)

50.9% 47.8%

MAPE (train)

MAPE (valid.)

Refitting the Linear Model

New Linear Model with lower constraints

65.2%

R - squared

\$57.6 \$59.4

RMSE (train)

RMSE (valid.)

22.6% 23.0%

MAPE (train)

MAPE (valid.)

MODEL COMPARISON Based on KPIs

Table comparing model performance metrics.

	Linear	Parsimony	Decision Tree	Random Forest	XG Boost
R-squared	65.2%	48.1%	71.0%	74.6%	74.3%
RMSE (train)	\$57.6	\$71.0	\$50.6	\$20.2	\$39.0
RMSE (validation)	\$59.4	\$70.1	\$53.4	\$49.4	\$49.3
RMSE (testing)	\$80.1	\$105.8	\$88.9	\$80.2	\$85.8
MAPE (train)	22.6%	31.9%	18.0%	6.9%	12.6%
MAPE (validation)	23.0%	29.8%	18.4%	16.8%	16.4%
MAPE (testing)	32.6%	48.8%	34.2%	32.4%	35.4%

BEST PERFORMING MODEL Deep dive

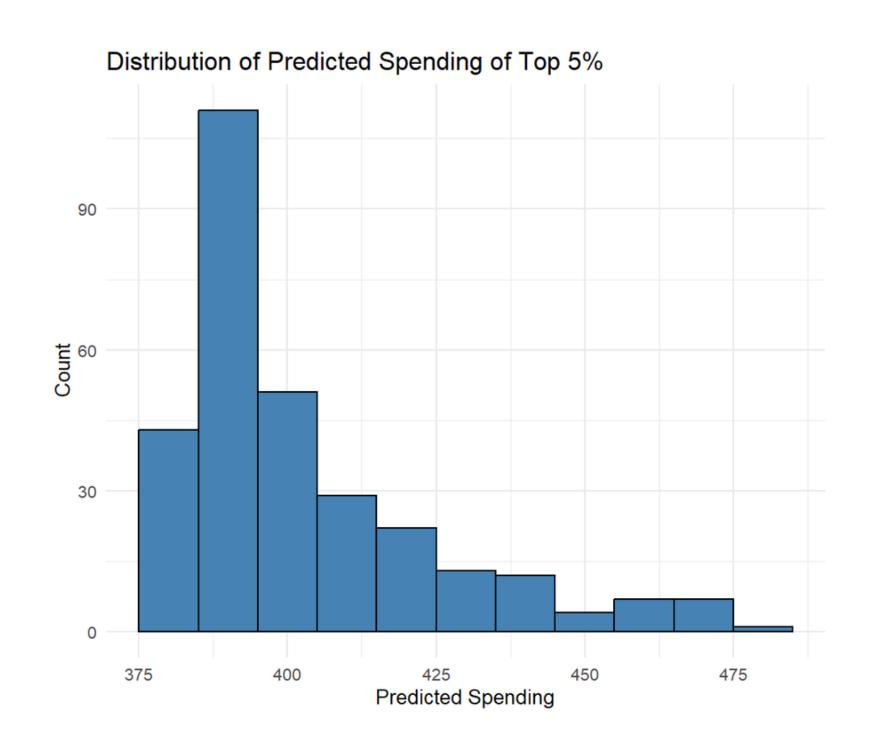
Interpretation of the model's key features and their influence

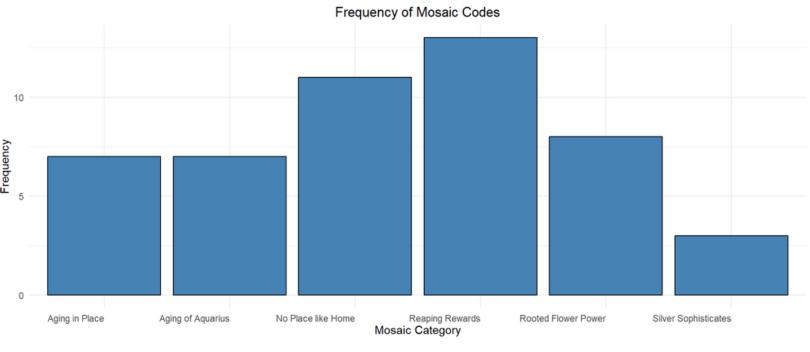
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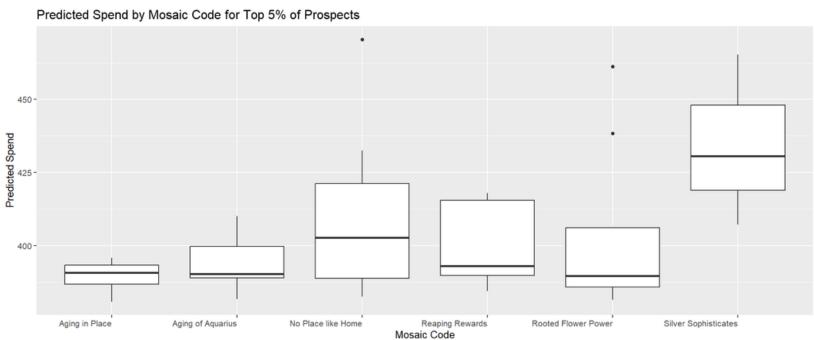
PROSPECTIVE ANALYSIS

Insights into prospective customer spending predictions.

Analysing the Top 5% of Prospects





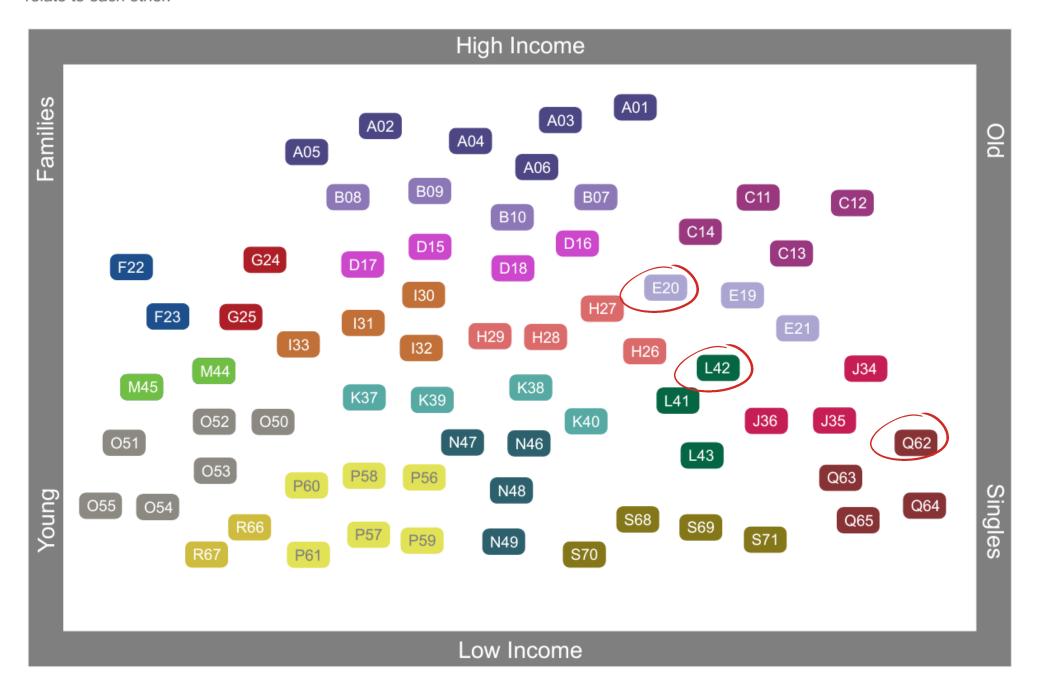


PROSPECTIVE ANALYSIS

Insights into prospective customer spending predictions.

Based on Mosaic Codes

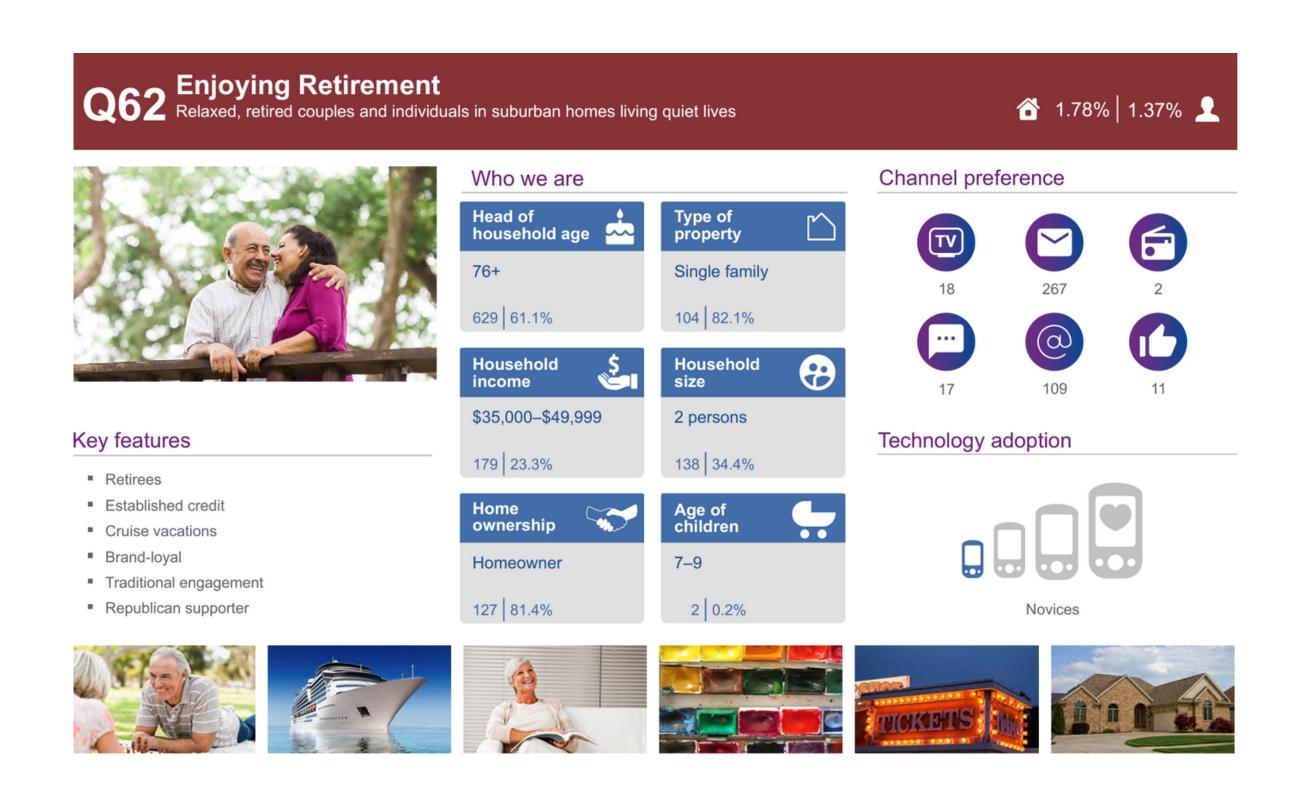
The Mosaic USA family tree illustrates the major demographic and lifestyle polarities between the groups and types, and shows how the Mosaic types relate to each other.



- 1.Q62 Repaing Rewards
- 2.E20 No Place like Home
- 3.L42 Rooted Flower Pot

PROSPECTIVE ANALYSIS

Insights into prospective customer spending predictions.



THANK YOU

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