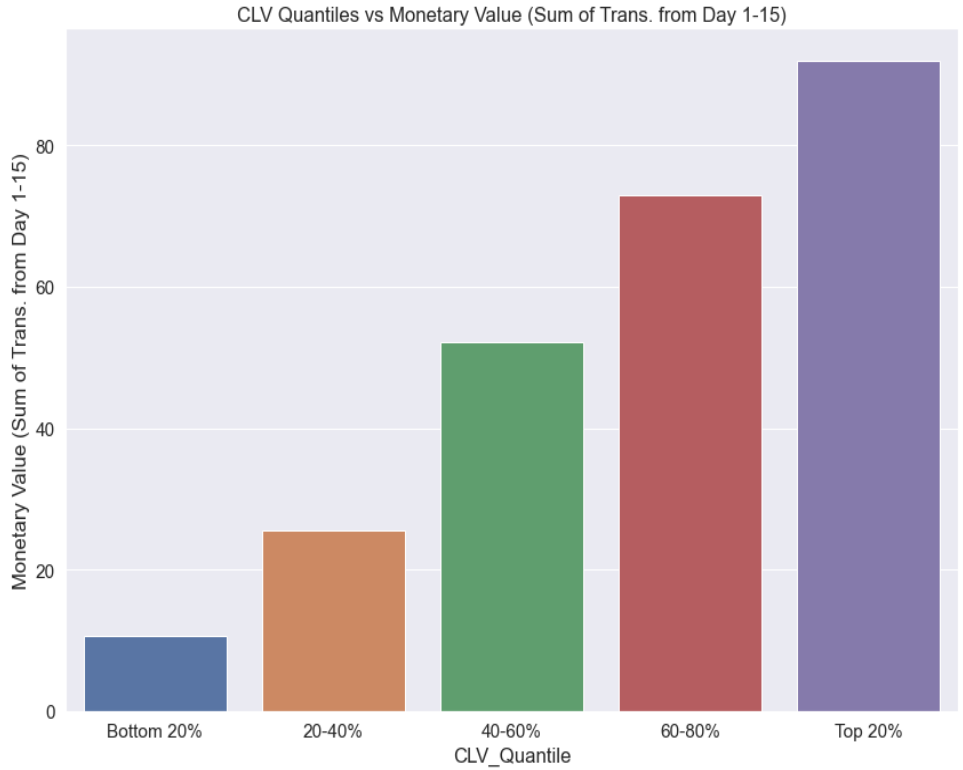
Segmenting Customers with Predictive CLV

Introduction

Companies spend a lot of money to acquire and retain customers. Data and customer lifetime value (CLV) help to identify which customers to retain and upgrade.

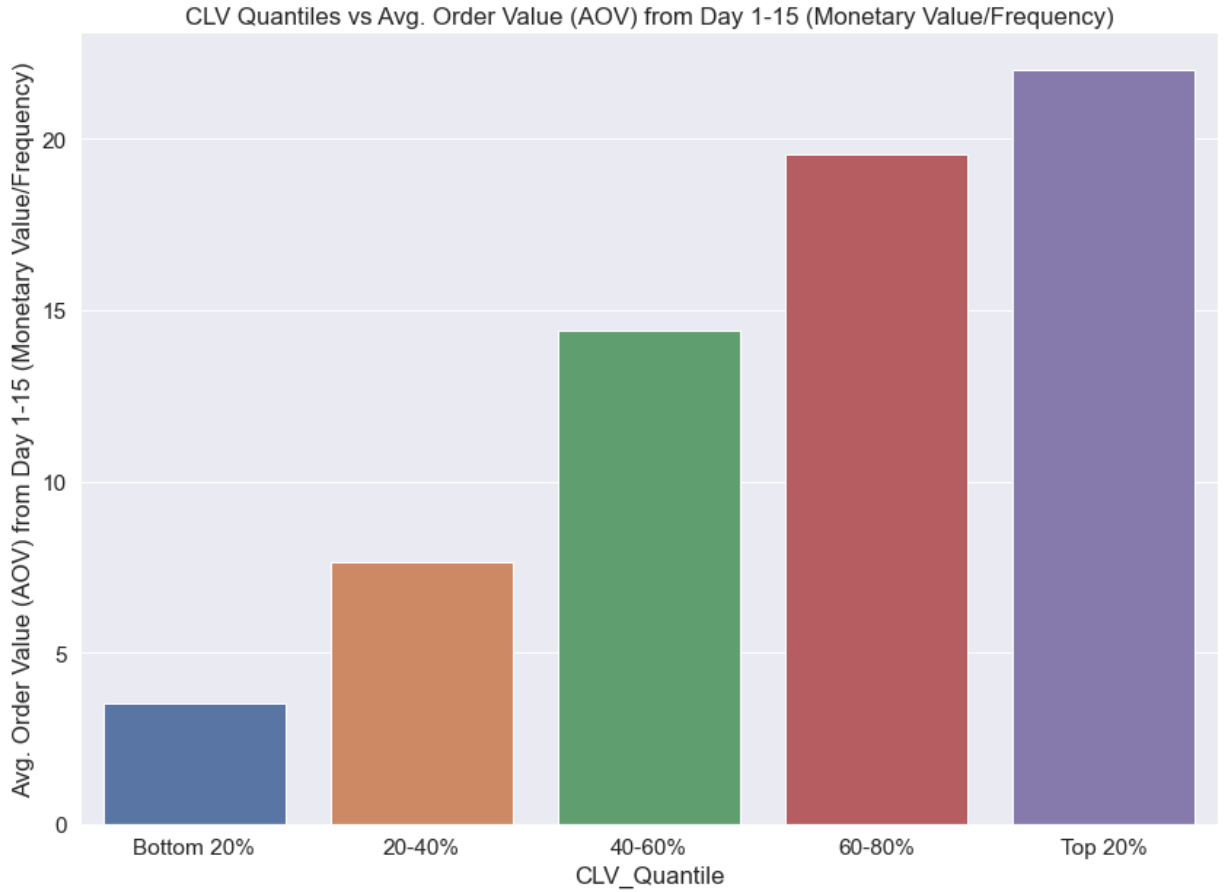
This data-driven approach will aim to leverage the power of predictive CLV to identify and segment the highest valued customers. This analysis will also dive into notable trends of the behaviors and demographics of the top 10% of customers. Furthermore, segmenting on CLV will enable us to tailor marketing strategies / loyalty programs to different customer segments, improving targeting, personalization, and overall customer satisfaction and loyalty.

Top 20% Most Valuable Customers spend $43/week on average

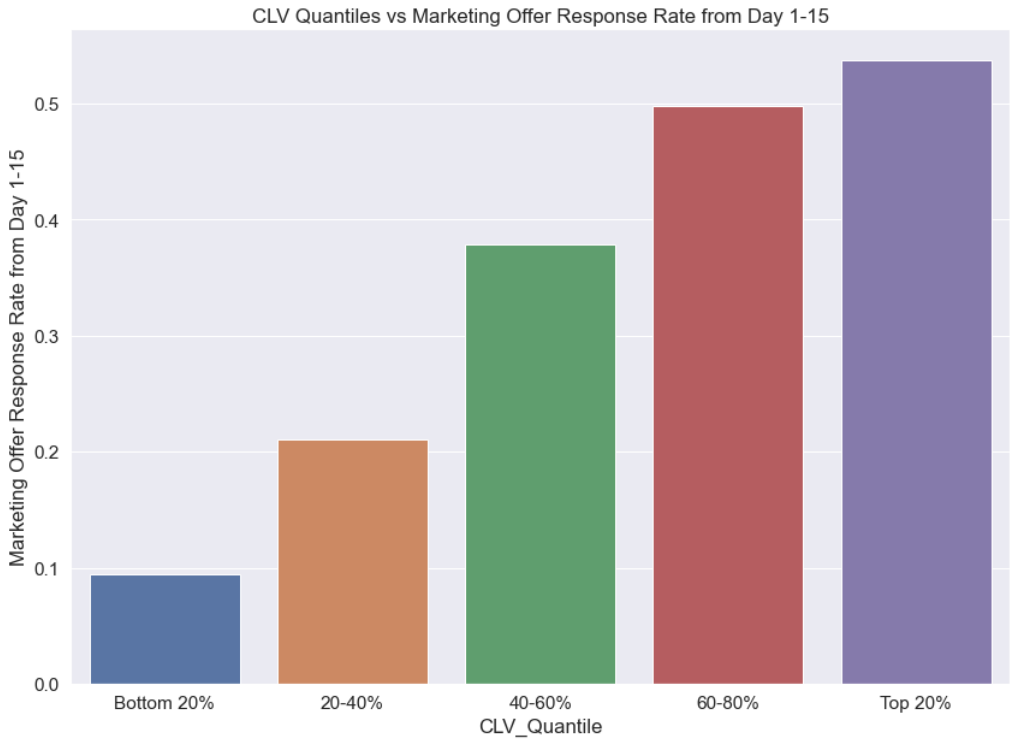


In terms of Recency, Frequency, and Monetary behaviors, the Top 80% of Starbucks customers visited as recently as 3 days before the measurement period was over and visited Starbucks 4 times from Day 1-15. The Top 20% spent at least $90 dollars from Day 1-15.

Top 20% spend ~$22/visit, Bottom 20% spend $3.5/visit on average, an $18.50 difference!

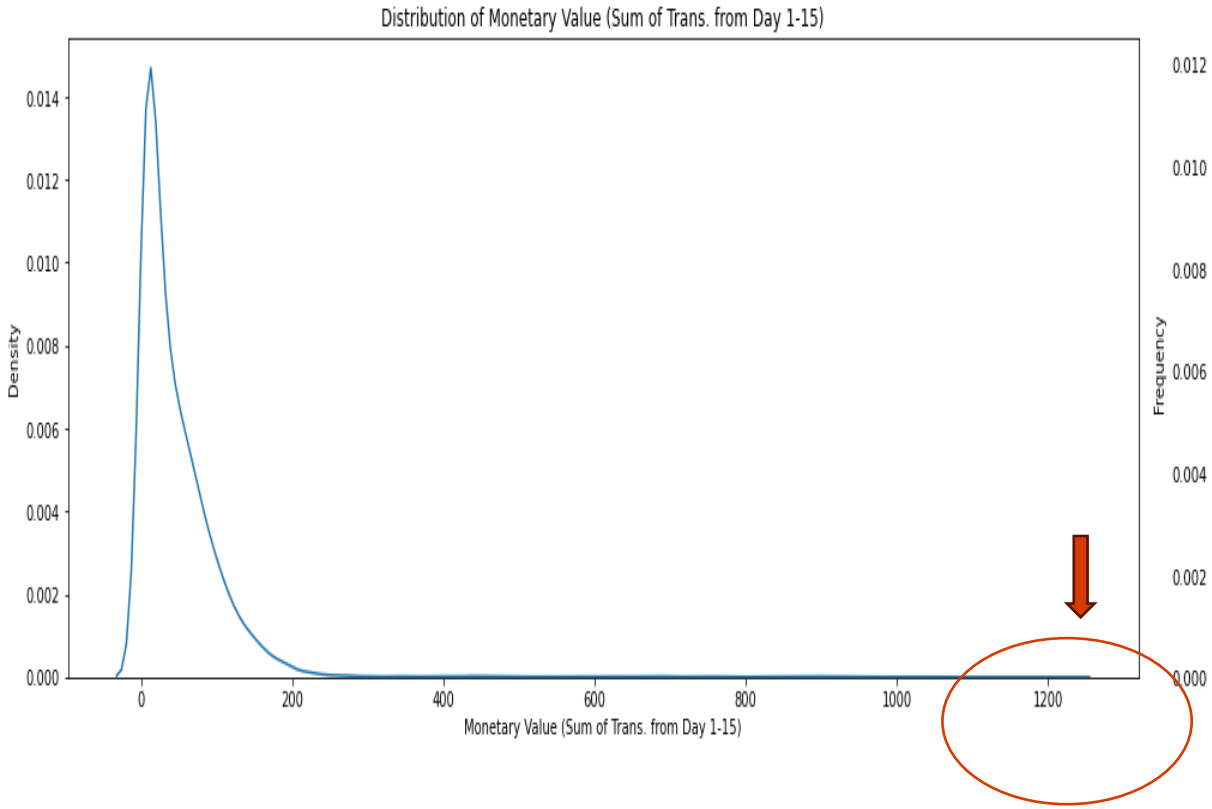


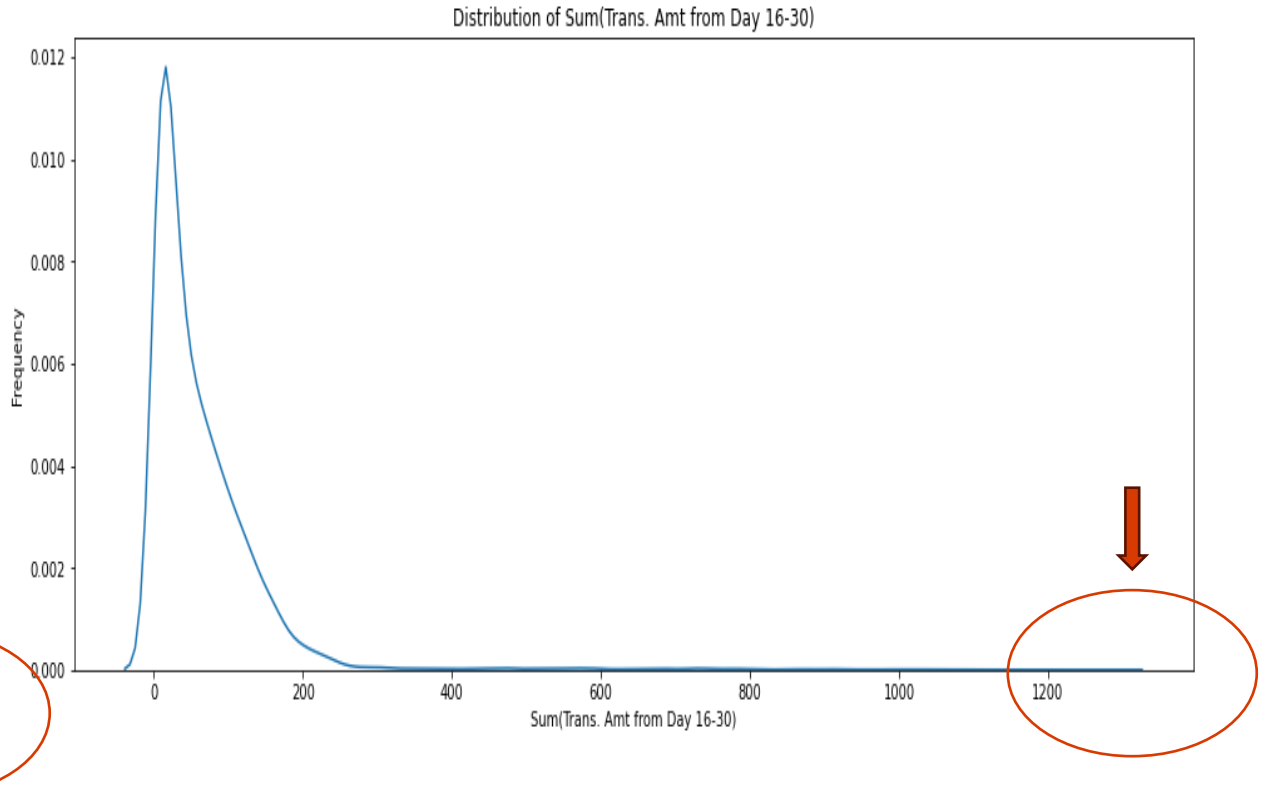
Response Rate is highly correlated with CLV, with a response rate difference of 44% between the Top 20% & Bottom 20%



As customer lifetime value (CLV) quantiles increase, there is a noticeable rise in the response rate, while the view rate remains relatively consistent across all quantiles. This finding indicates that customers, regardless of their lifetime value, have an equal likelihood of viewing the offer on average. It emphasizes the significance of response rate as a metric for measuring customer engagement.

CLV is highly right-skewed, some customers spend $1.2K-$1.3K in 15 days

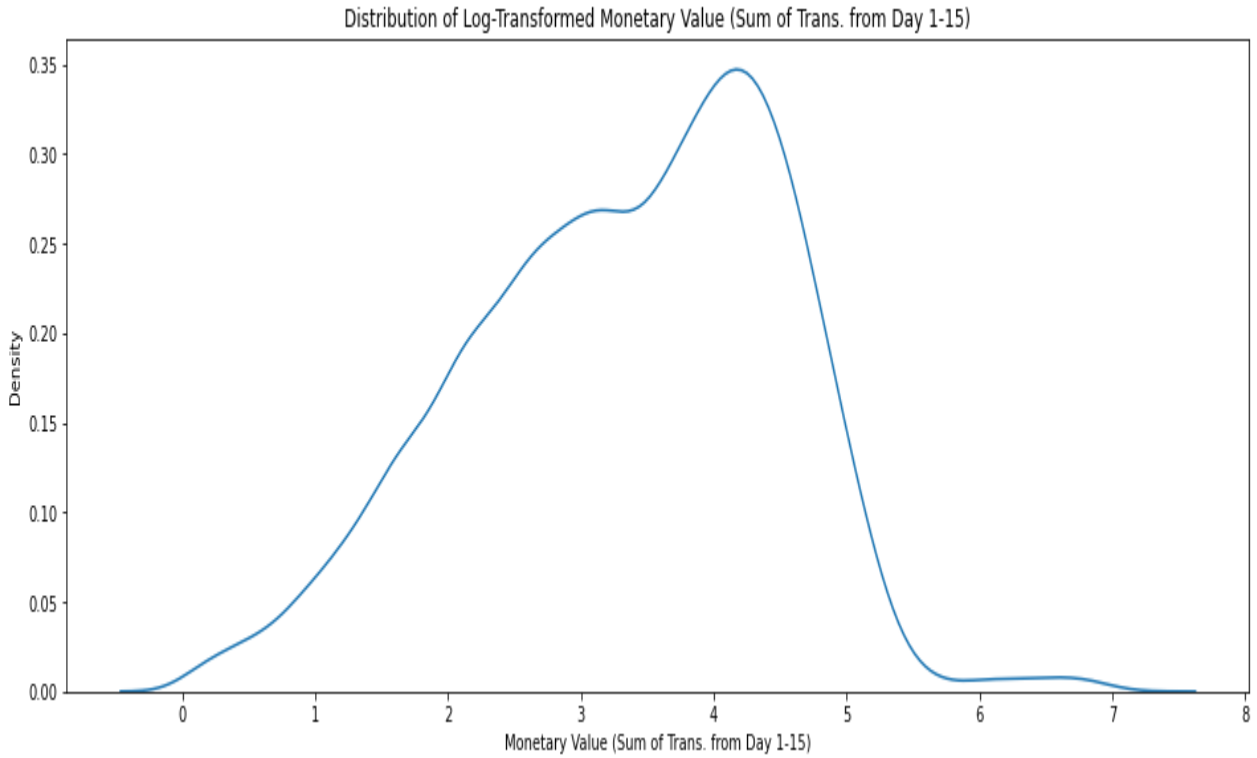


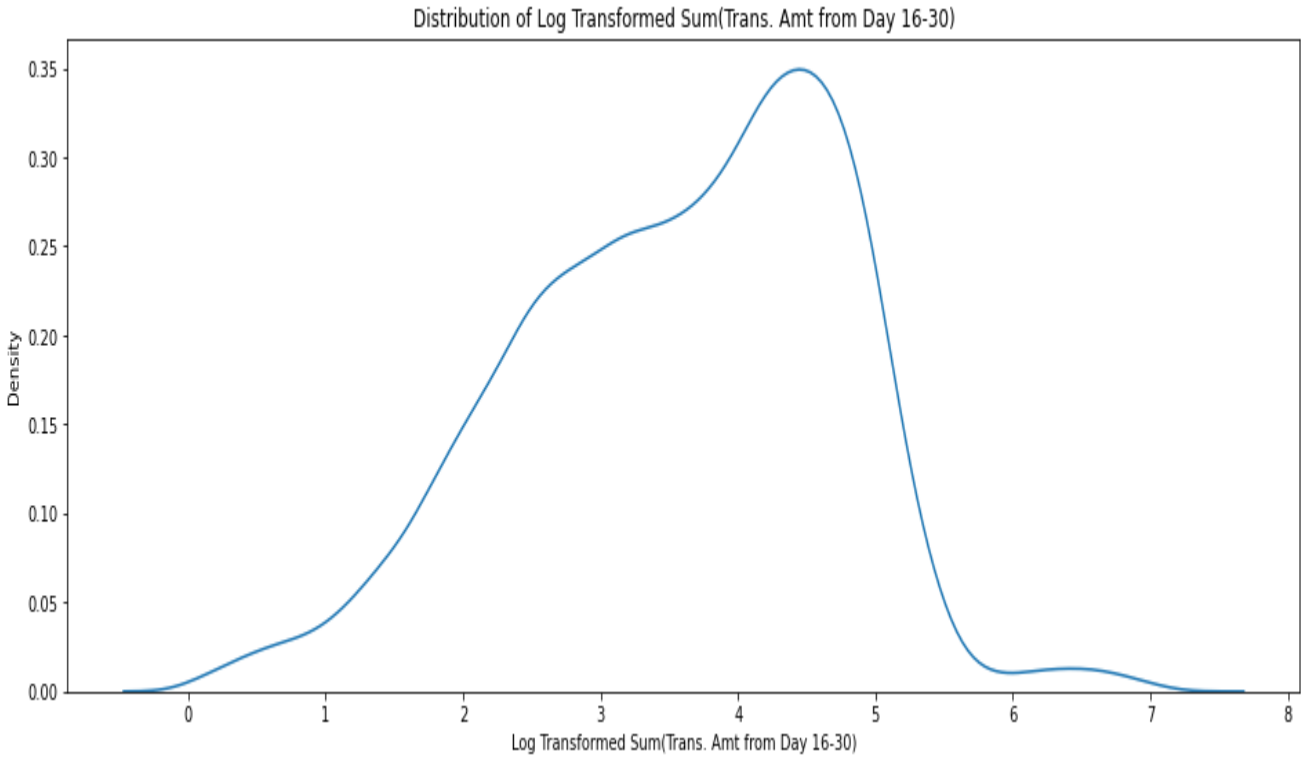


The median expenditure of a Starbucks customer was $30 from Day 1-15 and $40 from Day 16-30.

However, the max spend from Day 1-15 is $1.2K from Day 16-30 is $1.3K.

Applying Log Transformation to Monetary Value Feature & Target Variable reduces skewness





Log transformation may help reduce prediction errors measured by MAE of each quantile.

Unveiling Customer Profiles using Descriptive Statistics: Demographics, Buying Patterns, & Engagement Levels By Quantile

Occasional Buyers ($0.6M/yr)

Casual Shoppers ($1.6M/yr)

Regular Patrons ($3.3M/yr)

Engaged Members ($5.3M/yr)

Top Spenders ($9.6M/yr)

Customers	Gender (M/F Ratio)	Income Distribution (Top 2-3)	Average Frequency	Average Monetary Value (Day 1-15)	Average View Rate	Average Response Rate	Spent More of Less in Day 16-30 than Day 1-15	Average Sum of Transactions (Day 16-30)
Occasional Buyers (Bottom 20%) [$0-$14.65)	79% / 21%	30k-50k (56%), 50-75k (43%)	3	$12	58%	11%	Less	$6
Casual Shoppers (Bottom 20%-40%) [$14.65-$34.30)	69% / 31%	50-75k (47%), 30-50K (39%), 75-100k (11%)	4	$29	63%	24%	Less	$19
Regular Patrons (40%-60%) [$34.30-$64.49)	59% / 41%	50-75k (45%), 30-50k (29%), 75-100k (20%)	4	$53	68%	38%	Less	$40
Engaged Members (60-80%) [$64.49-$107.86)	49% / 51%	50-75k (42%), 75-100k (29%)	4	$73	71%	50%	More	$77
Top Spenders (Top 20%) [$107.86-$1287.25)	46% / 54%	50-75k (41%), 75-100k (37%)	4	$92	72%	54%	More	$179

Super Spenders vs Rest of Population: Demographics, Buying Patterns, & Engagement Levels

Rest of Population ($14.4M/year)

Super Spenders ($6M/year)

Customers	Gender (M/F Ratio)	Income Distribution (Top 3)	Average Frequency	Average Monetary Value (Day 1-15)	Average View Rate	Average Response Rate	Spent More of Less in Day 16-30 than Day 1-15	Average Sum of Transactions (Day 16-30)
Rest of Population (0-90%) [$0-$144.35)	60% / 40%	50-75k (44%), 30k-50k (30%), 75k-100k (20%)	4	$52	67%	36%	Less	$50
Super Spenders (Top 10%) [$144.35-$1,287.25)	44% / 56%	50k-75k (39%), 75k-100k (39%), 100k-120k (14%)	4	$97	72%	54%	More	$252

Insights from Super Spenders (Top 10%) Analysis

Spending Amount: The most significant finding is the difference in spending amounts between the Super Spenders and the Rest of the Population. In both halves of the month, Super Spenders spend considerably more than the Rest of the Population. Super Spenders have a significantly higher average sum of transactions in the second half of the month compared to the Rest of the Population ($252 vs $50).

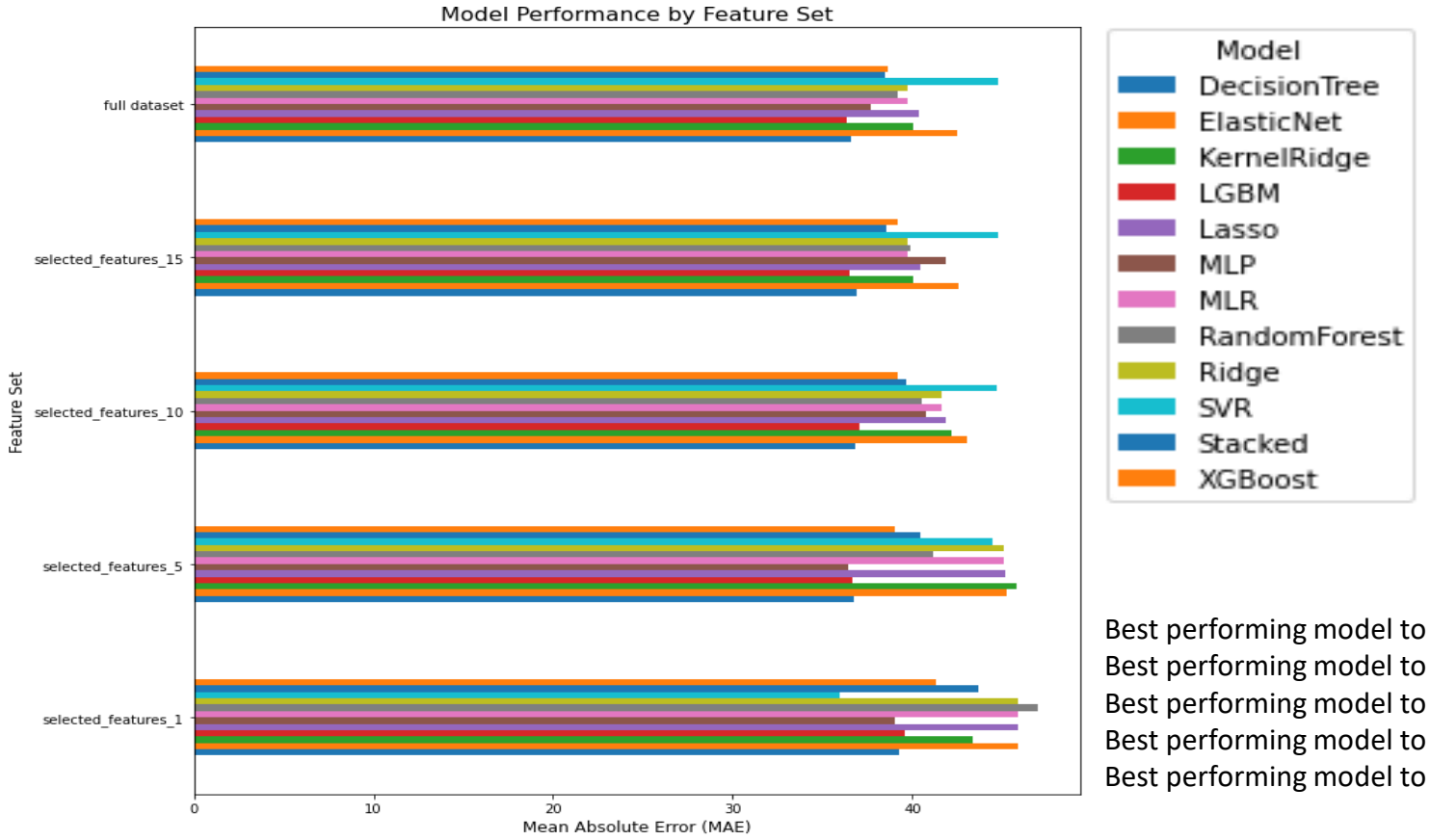
Response Rate: Super Spenders have a higher response rate than the Rest of the Population (54% vs 36%). This is a substantial difference and may indicate higher engagement or satisfaction among Super Spenders. **Action**: Are Super Spenders more responsive to certain types of marketing or specific products? Use this information to enhance customer engagement strategies.

Gender Distribution: Super Spenders have a higher proportion of females (56%) compared to the Rest of the Population (40%). This could indicate a gender bias in spending patterns. **Action**: Consider whether gender-specific marketing or product strategies could be beneficial.

Income Distribution: There's a difference in income distribution between the two groups, where there are considerably more individuals that make 75k and above in the Super Spender category. Spending patterns of Super Spenders are influenced by their disposable income.

Frequency of Transactions: Both groups have the same average frequency of transactions, suggesting that the total spend is more a function of amount per transaction than frequency. **Action**: Focus on strategies that increase the amount spent per transaction rather than the number of transactions.

Selected LGBM as Winner Model utilizing Full Feature Set

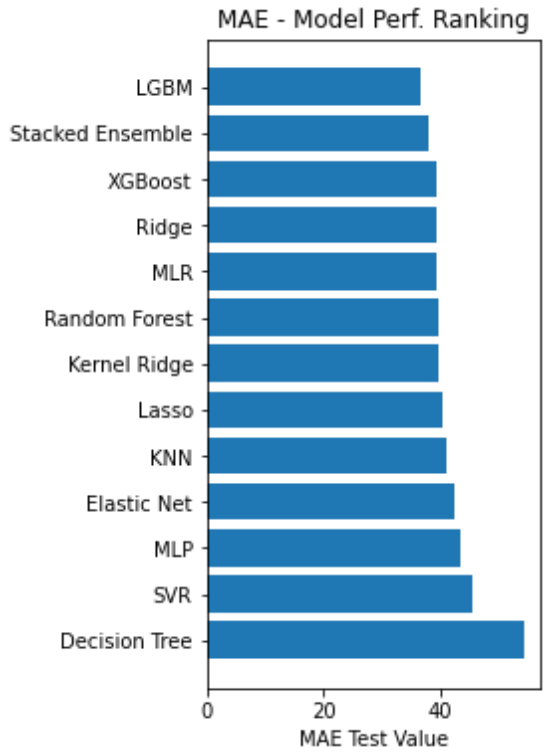


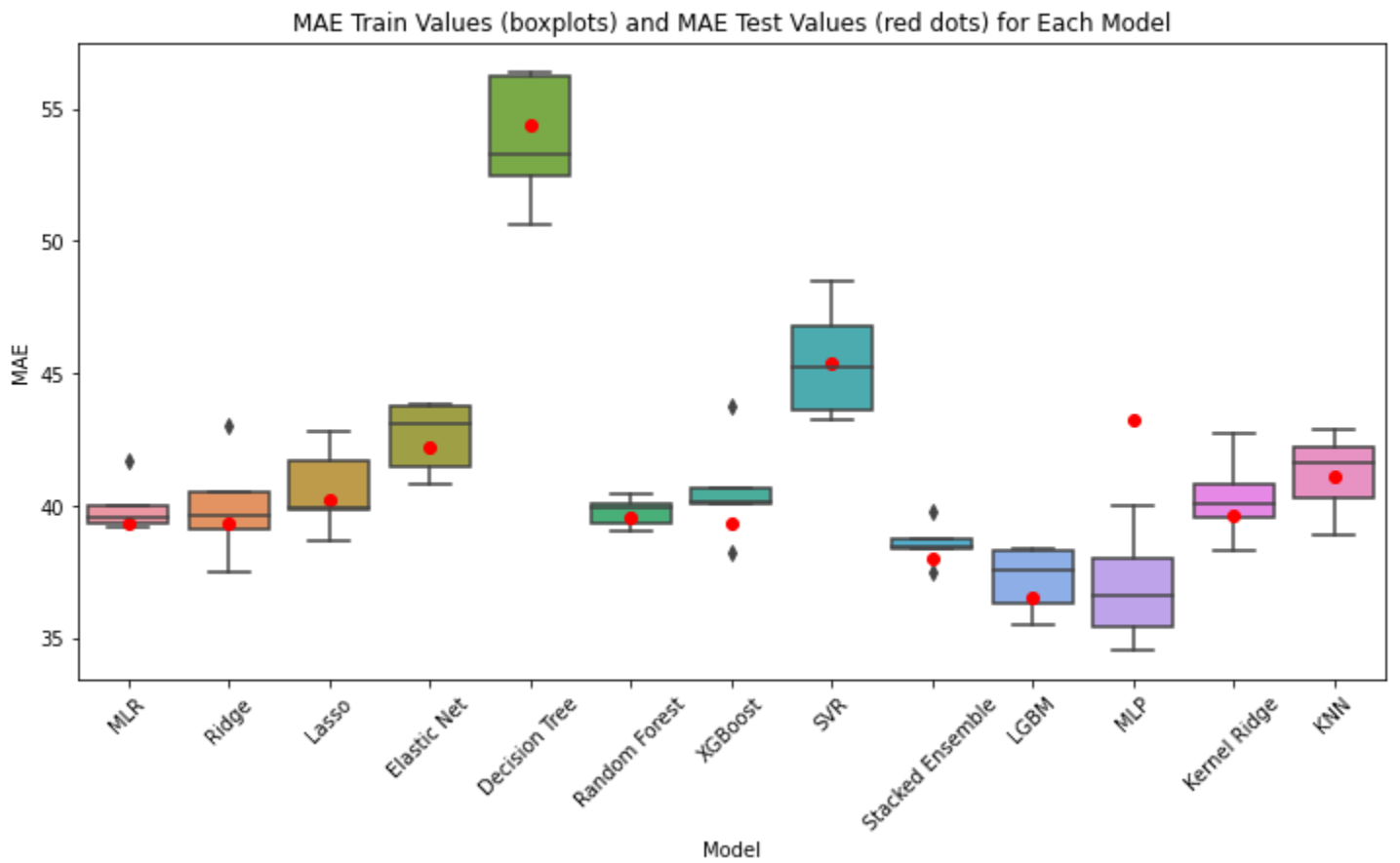
Best performing model to minimize MAE for full dataset: LGBM (MAE: 36.32)
Best performing model to minimize MAE for selected_features_15: LGBM (MAE: 36.50)
Best performing model to minimize MAE for selected_features_10: DecisionTree (MAE: 36.84)
Best performing model to minimize MAE for selected_features_5: MLP (MAE: 36.42)
Best performing model to minimize MAE for selected_features_1: SVR (MAE: 35.96)

Note: AOV and offers completed by channel features are dropped upfront to reduce multicollinearity because they are derived from existing columns in the dataset.

Selecting LGBM with the full dataset is a good decision because it performed relatively well, with an MAE of 36.32. Using the complete dataset helps LGBM capture complex patterns and provide more accurate predictions.

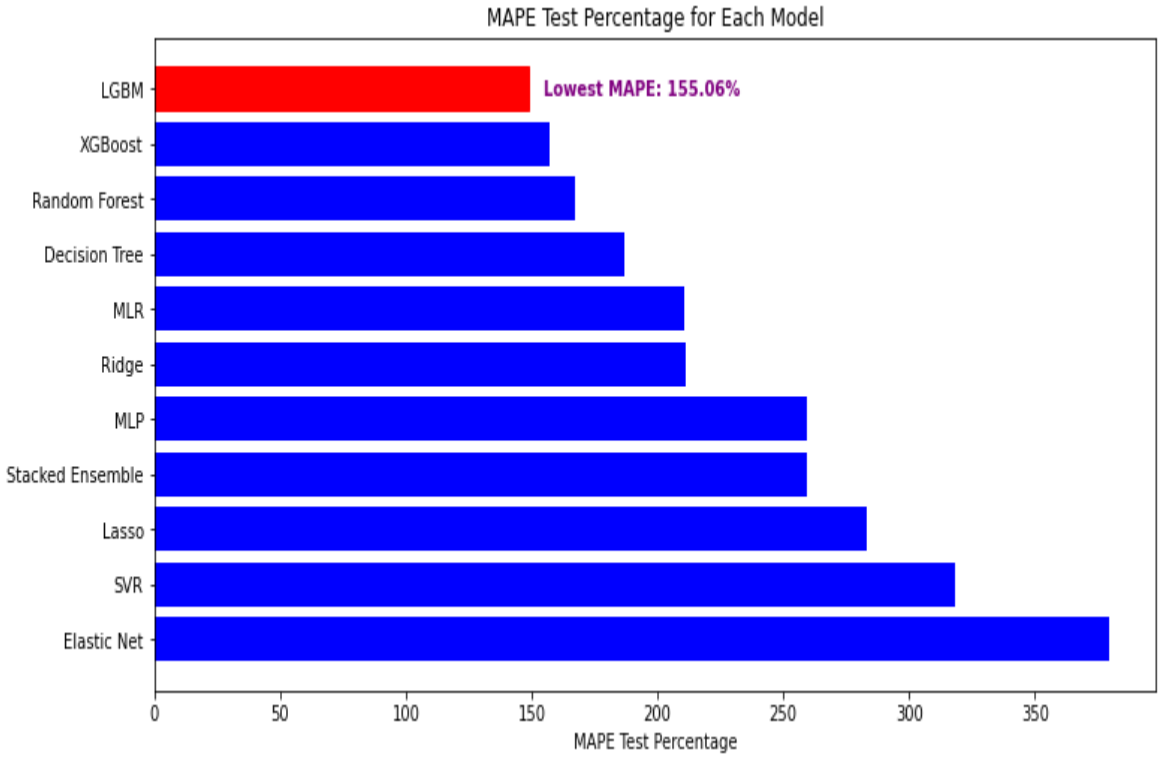
LGBM emerged as Winner Model during model comparisons by minimizing Test MAE and maintaining a lower MAE range in K-fold cross-validation

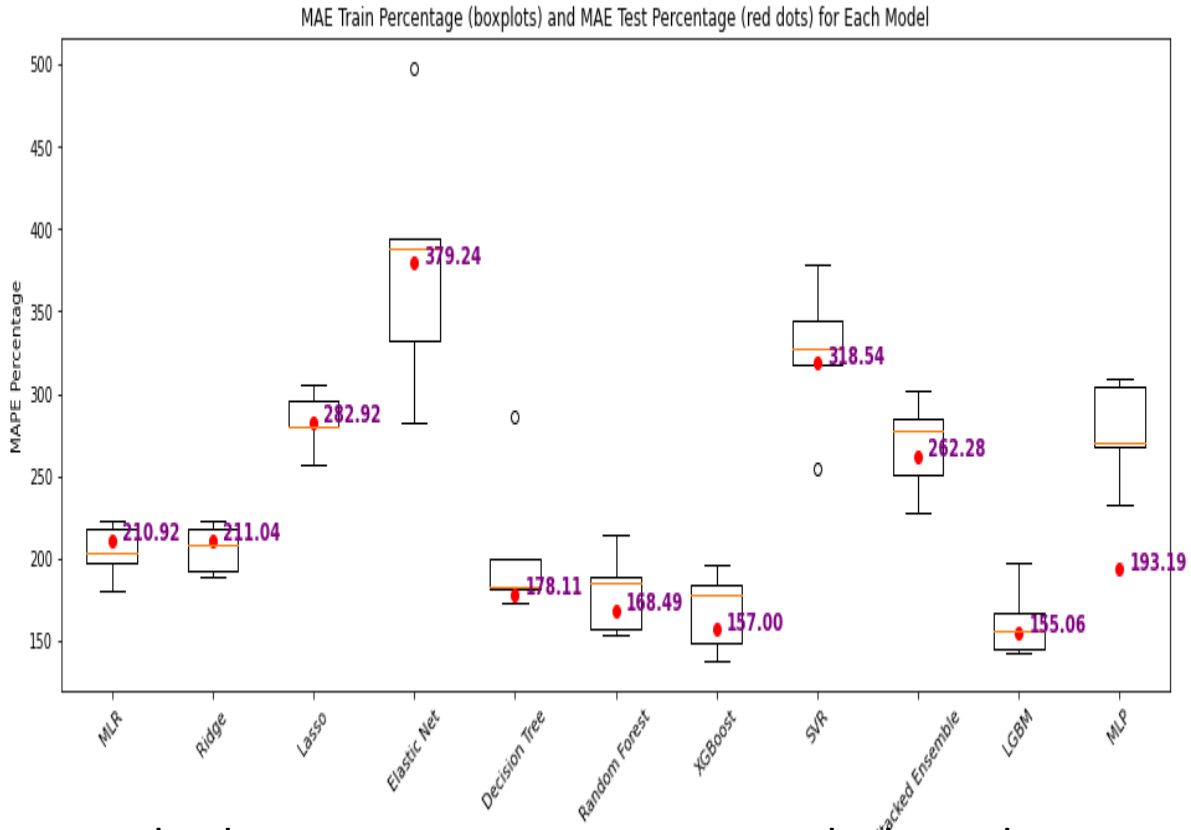




LGBM model is chosen because it minimizes the MAE. For Kfold CV=5, Shuffle=True, the MAE Train value range is lower and MAE Test value is the lowest vs other models. MAE measures how close the predicted values are to the actual values on average.

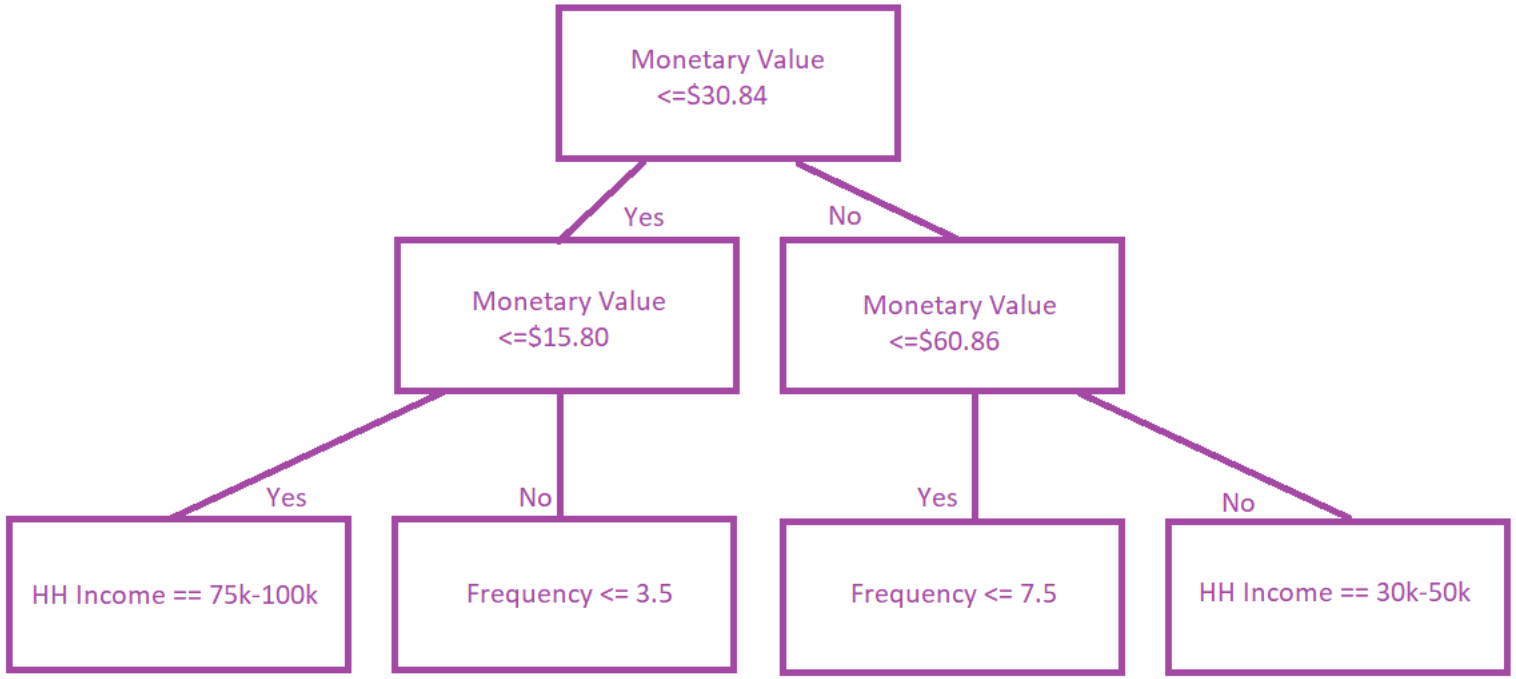
LGBM emerged as Winner Model during model comparisons by minimizing Test MAPE and maintaining a lower MAPE range in K-fold cross-validation





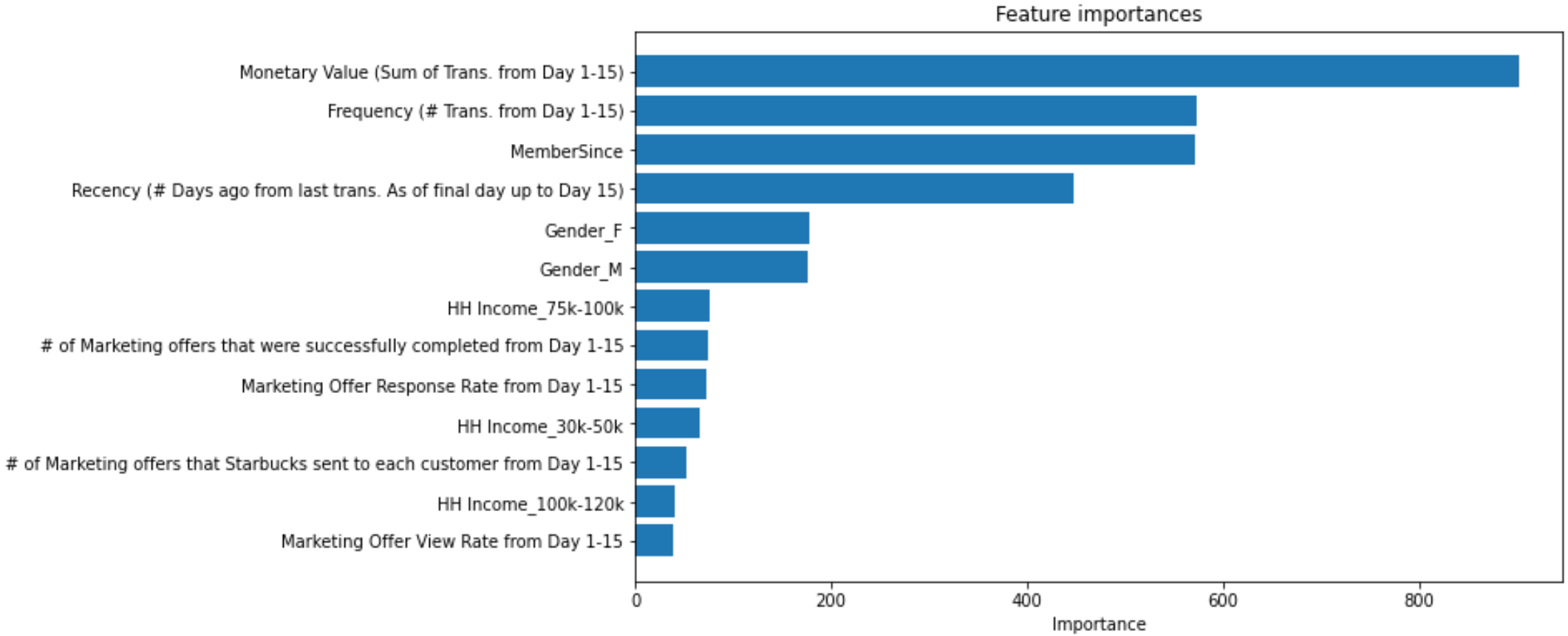
LGBM model is chosen because it minimizes the MAPE, the mean absolute percentage error. MAPE calculates the average percentage difference between the predicted & actual values. For Kfold CV=5, Shuffle=True, the MAPE Train percentage range is lower and narrow indicating model stability and the MAPE test percentage is the lowest vs other models.

LGBM Tree Splits analyzes Spending, HH Income, Frequency in initial branches, identifying influential predictors



Initial splits capture important predictors. By considering these key features early on, the algorithm can identify the most relevant variables and create a strong foundation for subsequent splits. This approach allows for more effective and efficient decision-making, potentially leading to improved predictions and model performance.

LGBM Feature Importance is consistent with tree splits insights



Winner Model: LightGBM without log transformation predicts Regular Patrons (60-80% Quantile) the best, predictions impacted by skew

Quantile	Avg. Actual CLV	Avg. Predicted CLV	MAE	MAPE
Bottom 20%	$10.81	$18.01	22.83	129.8%
20-40%	$26.0	$40.38	33.33	87.4%
40-60%	$54.95	$82.1	26.57	37.2%
60-80%	$99.23	$107.49	24.76	21.2%
80-90%	$135.07	$117.79	46.28	30.5%
90-95%	$169.55	$126.67	109.94	47.7%
95-99%	$435.8	$144.45	631.54	85.7%

The model shows a skew in CLV predictions, overestimating for the Bottom 80% and underestimating for the Top 20%. This is due to an uneven distribution of customers, with a higher concentration of lower-spending customers and relatively fewer high-spending customers, resulting in a weaker signal from the super spenders. Consequently, the tree model struggles to identify meaningful patterns or splits specific to the relatively fewer high-value customers, impacting its ability to accurately capture their behaviors. As a result, the model has difficulty predicting the lowest or highest value customers.

The model consistently under predicts CLV for Super Spenders (Top 10% Actual CLV is $144+) because of right-skew.

User	Predicted CLV	Actual CLV	Difference
User 1	$114.33	$170.93	-56.6
User 2	$122.75	$201.84	-79.09
User 3	$127.28	$195.37	-68.09
User 4	$107.98	$219.99	-112.01
User 5	$78.39	$350.43	-272.04
User 6	$104.73	$171.51	-66.78
User 7	$107.25	$436.78	-329.53
User 8	$120.03	$183.9	-63.87
User 9	$115.78	$173.68	-57.9
User 10	$143.81	$172.54	-28.73

Applying 95% Cap on Monetary Value & Target Variable improved MAE & MAPE for Top 10% and Bottom 60%

Quantile	Avg. Actual CLV	Avg. Predicted CLV	MAE	MAPE
Bottom 20%	$10.81	$15.51	18.71	105.8%
20-40%	$26.0	$36.77	27.14	71.7%
40-60%	$54.95	$72.06	19.88	27.7%
60-80%	$99.23	$93.89	30.80	26.2%
80-90%	$135.07	$102.38	59.30	39.1%
90-95%	$169.55	$109.17	78.48	45.8%
95-99%	$171.24	$118.5	78.67	45.9%

Applying a 95% Cap on the Monetary feature and Y target variable improves predictions for the Top 10% and Bottom 60% segments, also resulting in similar MAE and MAPE errors for the Top 10%.

Applying a Log Transformation on the Monetary Value & Target Variable to this dataset do not improve predictions for High-Value Segments

Quantile	Avg. Actual CLV	Avg. Predicted CLV	MAE	MAPE
Bottom 20%	$10.81	$11.21	16.94	88.6%
20-40%	$26.00	$30.79	22.33	55.5%
40-60%	$54.95	$62.64	20.89	26.8%
60-80%	$99.23	$85.54	41.41	34.0%
80-90%	$135.07	$94.60	74.27	47.1%
90-95%	$169.55	$99.94	151.27	62.0%
95-99%	$435.80	$110.89	657.88	88.9%

Log transformation reduces the variability in error metrics across quantiles and improves predictions for the Bottom 60% of customers. However, its performance is less effective in predicting the Top 40% or high-value customers. Therefore, log transformation is not necessary for this dataset.

Applying a 95% Cap AND Log Transformation on the Monetary Value & Target Variable to this dataset do not improve predictions for High-Value Segments

Quantile	Avg. Actual CLV	Avg. Predicted CLV	MAE	MAPE
Bottom 20%	$10.81	$8.23	12.36	70.5%
20-40%	$26.00	$20.31	21.59	56.2%
40-60%	$54.95	$40.91	27.04	36.0%
60-80%	$99.23	$72.13	53.28	45.7%
80-90%	$135.07	$84.74	83.63	55.4%
90-95%	$169.55	$91.82	102.40	59.8%
95-99%	$171.24	$101.16	102.13	59.6%

Consistent with the prior slide, log transformation reduces the variability in error metrics across quantiles and improves predictions for the Bottom 40% of customers. However, it does not perform as well in predicting the Top 40% or high-value customers. Therefore, log transformation is not necessary for this dataset.

Is modeling necessary to improve predictions? While past spend appears to be a good signal for future spend to segment users on CLV, without modeling, error metrics are worse.

Quantile	Avg. Actual CLV	Avg. Predicted CLV	MAE	MAPE
Bottom 20%	$10.81	$8.65	17.67	99.9%
20-40%	$26.0	$21.07	33.33	87.0%
40-60%	$54.95	$44.57	41.75	55.4%
60-80%	$99.23	$78.63	60.64	51.9%
80-90%	$135.07	$110.27	81.53	54.0%
90-95%	$169.55	$141.66	131.01	58.2%
95-99%	$435.8	$245.66	653.16	89.2%

This approach only uses the monetary value from the first 15 days feature to forecast the sum of transactions from the 16th to 30th day without any predictive modeling.

Insights and Actionable Recommendation

The best method to improve predictions was using a hyper-parameter tuned LGBM model and applying 95% Cap on Monetary Value & Target Variable. This improved MAE & MAPE for Top 10% and Bottom 60%.

To address the right skew in the data, a log transformation was tested on the Monetary Value and Target Variable. While this transformation successfully reduced variability in error metrics and improved predictions for the Bottom 40% of customers, it surprisingly struggled in predicting the Top 40%. Therefore, the log transformation did not assist in predicting high-value segments with this dataset. It's worth noting that the dataset has limitations, as CLV is usually measured over a longer time horizon or with a richer set of features.

While past spend appears to be a good signal for future spend to segment users on CLV, without modeling, MAE and MAPE error metrics are worse. Utilizing predictive modeling is the preferred approach for CLV segmentation.

Identifying super spenders (Top 10% CLV) allows businesses to prioritize high-value customers and implement customized strategies. To identify these super spenders, one can set the quantile at 90% and calculate the mean of the Target Variable within the 90-100% range. This approach enables effective customer segmentation and empowers the execution of targeted marketing campaigns that drive improved business outcomes.

Since the average frequency of purchases is similar between the Top 10% and the rest of the population, it is recommended to focus on strategies that increase the amount spent per transaction (Average Order Value) rather than the number of transactions.

Future Work

Introduce Starbucks Diamond Loyalty Program

By keeping outliers, we have retained valuable information for future work. We can implement a tailored loyalty program, Starbucks Diamond, for "super spenders" in the top 10% of CLV. As a short-term strategy, we can include customers spending $200 or more per month. As a long-term strategy, we can identify and target potential upgraders using a binary classification program. The focus would be on identifying and targeting users who display behaviors indicating their likelihood to upgrade to this program. This is useful because identifying high-value customers and retaining them is typically more cost-effective than acquiring new ones.

Prioritize Regular Patrons (60-80% Quantile) as a Retention Strategy

As the LGBM model without preprocessing (without 95% Cap or Log Transformation) predicts the Regular Patrons (60-80% Quantile) segment the best with the lowest errors, we can focus on encouraging these customers to transition into higher-value segments. Note that the Engaged Members and Top Spenders segments exhibit strong response rates and spending habits, so they would require less attention in terms of retention efforts.

Use K-Means Clustering to Create Models for Each Customer Segment

Utilize K-Means Clustering to create customer segment models, enabling personalized experiences and targeted communications. This approach allows businesses to focus on valuable segments, allocate resources effectively, and inform feature prioritization in product development.

THANK YOU!

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