ML to Improve Marketing ROI

MIDS 207 Spring 2025 Section 6 Final Project

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Business Context

Customer Experience Excellence (CX)

- Critical component of strategic priorities for companies across sectors
- Must adapt these for all customer demographics — Gen-Z, Millennials, Senior Citizens
- Need to innovate on CX across channels, product lines, and market segments.

Comparison with other work

- Previous work has used Lifetime Value (LFTV) and churn predictive models in industry to reduce Marketing Selling, General, and Administrative (SG&A) tasks
- Ongoing focus for incorporating varying data sets to improve commercial performance of Machine Learning engines for this task continues
- From our research, there is little to no research on the combination of customer segmentation with LFTV and churn models to improve campaign performance

Business Context and Opportunity

Key Definitions

- Customer Experience (CX): Overall perception a customer has across all touchpoints with a brand.
- Churn Prediction: Identifying customers likely to stop engaging or purchasing.
- Lifetime Value (LFTV): Total net profit attributed to the entire future relationship with a customer.

Business Problem

- Companies struggle to personalize CX across diverse demographics.
- Generic marketing campaigns lead to low engagement and poor ROI.
- Churn and LTV insights are often underutilized or siloed in strategy.

Opportunity

- Use machine learning to integrate churn, LTV, and segmentation into one unified pipeline.
- Deliver personalized, data-driven marketing to improve ROI and customer retention.
- Enable smarter allocation of campaign budgets toward high-value customers.

History, Data Challenge, Past research

Customer Experience Excellence (CX)

- Critical component of strategic priorities for companies across sectors
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Comparison with other work

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History, Data Challenge, Past research

What Industry Has Tried

- Applied LFTV models to optimize marketing spend and customer prioritization.
- Used churn models to flag at-risk users and reduce SG&A costs.
- Efforts often focus on individual models -segmentation, LFTV, or churn - not all three together.

Ongoing Challenges

- Limited research combining customer segmentation + LFTV + churn into one strategic ML framework.
- No clear pipeline for using these combined insights to drive campaign performance or ROI.

Our Question

Our Goal: Improvement of Marketing Campaign ROI

From this scope, in this work we address two questions:

- How can a Retail Chief Marketing Officer **improve their marketing campaign ROI** by launching effective intervention campaigns informed from Machine Learning models for customer lifetime value (LFTV) calculation and churn prediction?
- Does the use of Machine Learning defined Customer Segmentation improve model accuracy?

Impact: A repeatable ML engine that can continuously incorporate new data to improve campaign performance and learn from the market can be a tremendous asset for any company.

Our Question

Our Goal: Improve marketing campaign ROI through a unified ML-driven approach

From this scope, in this work we address two questions:

- How can a Retail Chief Marketing Officer **improve their marketing campaign ROI** by launching targeted intervention campaigns based on machine Learning models for customer **lifetime value (LFTV) calculation** and **churn prediction**?
- Does integrating machine-learned Customer Segmentation improve the accuracy and effectiveness of these predictive models?

Impact: A repeatable ML engine that can continuously incorporate new data to improve campaign performance and learn from the market can be a tremendous asset for any company.

Our Algorithms

Churn Prediction

Goal: Predicting whether a customer will stop using the company's products

Highest Correlation with Target: Tenure, Complaint, Marital Status

Final model: Random Forest Classifier with Grid Search

Validation Accuracy: 95%
AUC: 98%
Improvement over baseline: 32.51%

Customer Lifetime Value

Goal: Determine customer lifetime value based on purchasing habits (continuous variable)

Highest Correlation with Target: Purchase frequency, membership years, purchase value

Final model: Feed Forward Neural Network with Feature Selection

Validation RMSE: 23.07%
Improvement over baseline: 74.9%

Customer Segmentation

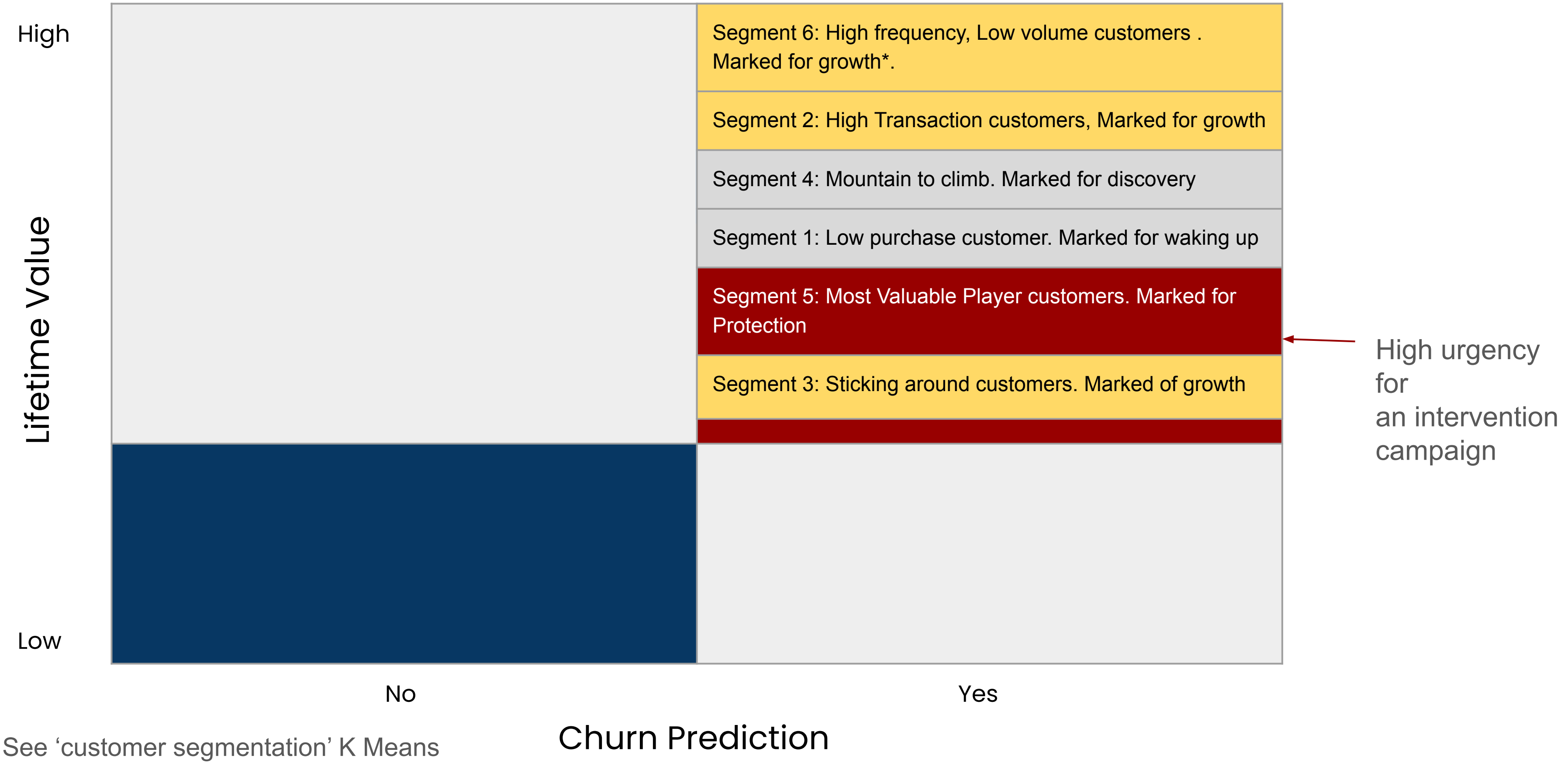
Goal: Understand customer demographics and consumption patterns via clustering algorithms.

Final model: K-Means with 6 clusters

Output: 6 Customer segments with meaningful action steps

Inertia**:** 2.94 on elbow-selected 6 clusters

Vision combines all three – LFTV, Churn, and Segmentation – to identify urgency of marketing action



* See 'customer segmentation' K Means section for complete segment definitions

Churn Prediction

Data Statistics and Preprocessing

Source:
https://www.kaggle.com/datasets/ankitverma2010/ecommerce-customer-churn-analysis-and-prediction/data

Key Statistics:

Initial Shape:
After cleaning and EDA: (5630, 9)

Churn Model Data Cleaning

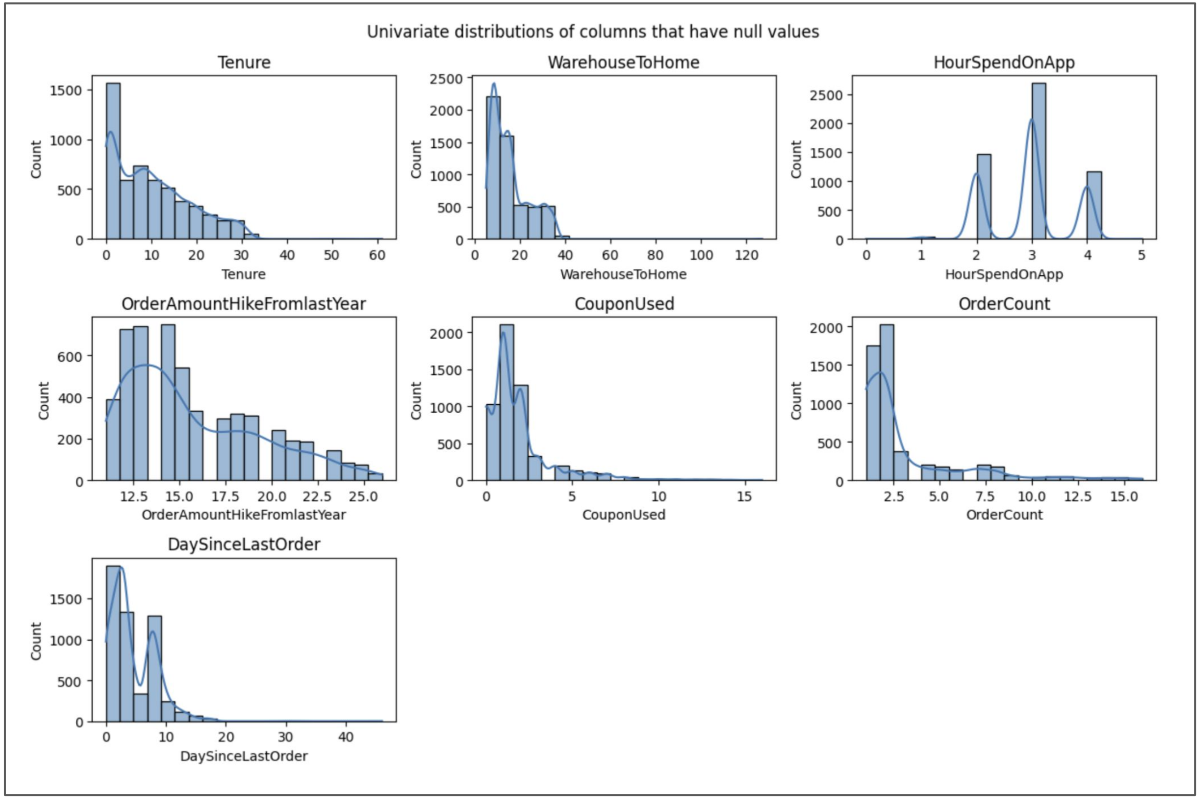
33% of the data had at least one null value in the row

The data to the right are the distributions of variables with null values

Since none had a normal distribution, we **imputed** null values using the **median**, which is better for skewed distributions

Additionally, we **One-Hot Encoded** the following categorical variables:

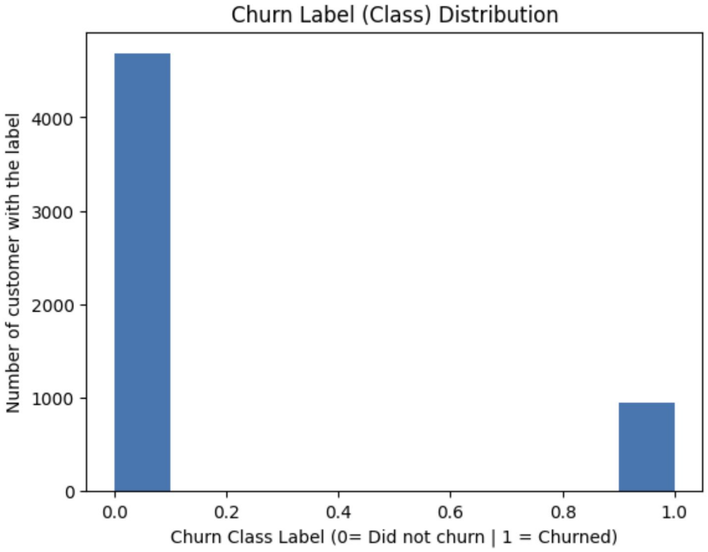
- Preferred Login Device
- Preferred Payment Mode
- Gender
- PreferedOrderCat
- Marital Status'



Churn Model EDA

Distribution of Churn Model Target Variable

~83% not churned, ~16% churned
After SMOTE: ~71% not churned, ~29% churned



Variables with the Highest Correlation to Churn

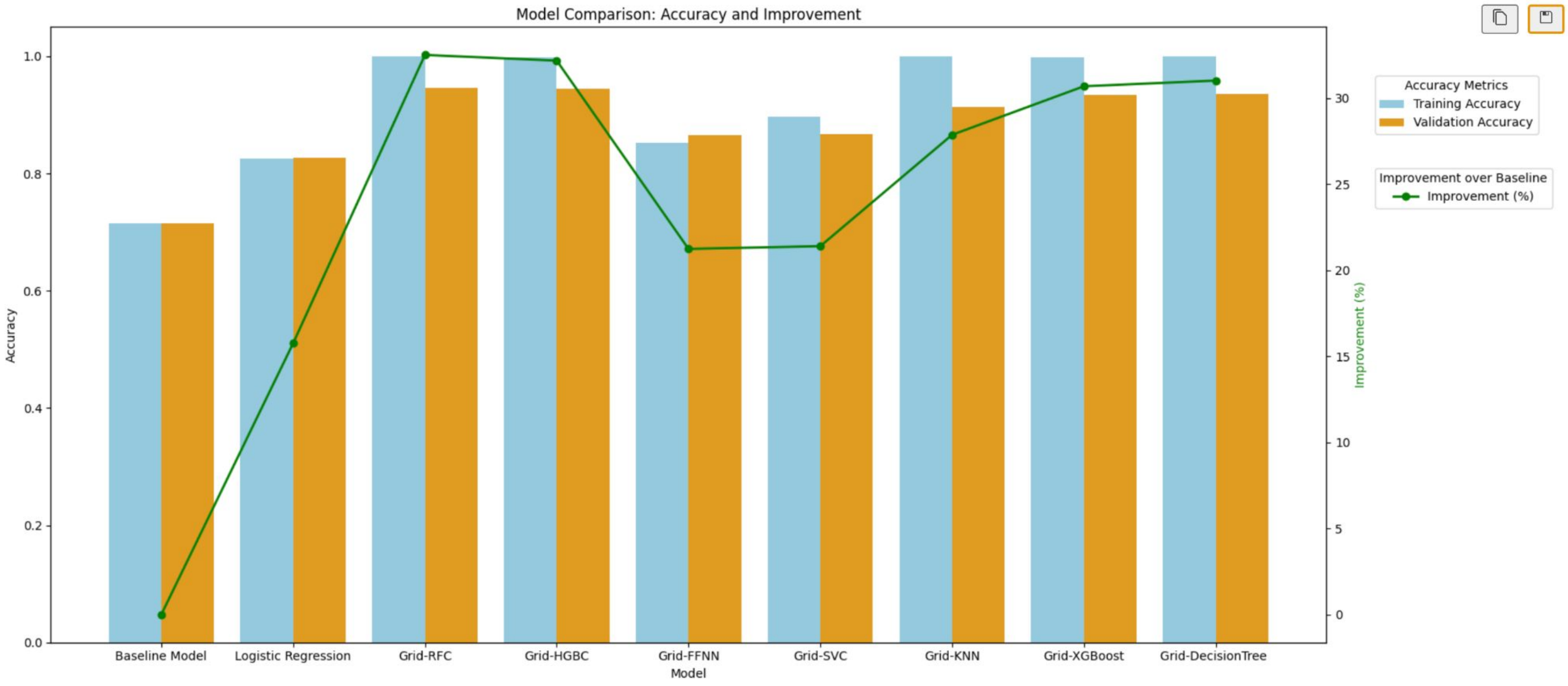
Dropped columns with corr < 0.1 to reduce noise

SatisfactionScore	0.105481
NumberOfDeviceRegistered	0.107939
PreferredLoginDevice_Mobile_Phone	0.111639
PreferedOrderCat_Mobile	0.113364
PreferedOrderCat_Laptop_and_Accessory	0.133353
CashbackAmount	0.154118
PreferedOrderCat_Mobile_Phone	0.154387
DaySinceLastOrder	0.155871
MaritalStatus_Single	0.180847
Complain	0.250188
Tenure	0.337831
Churn	1.000000

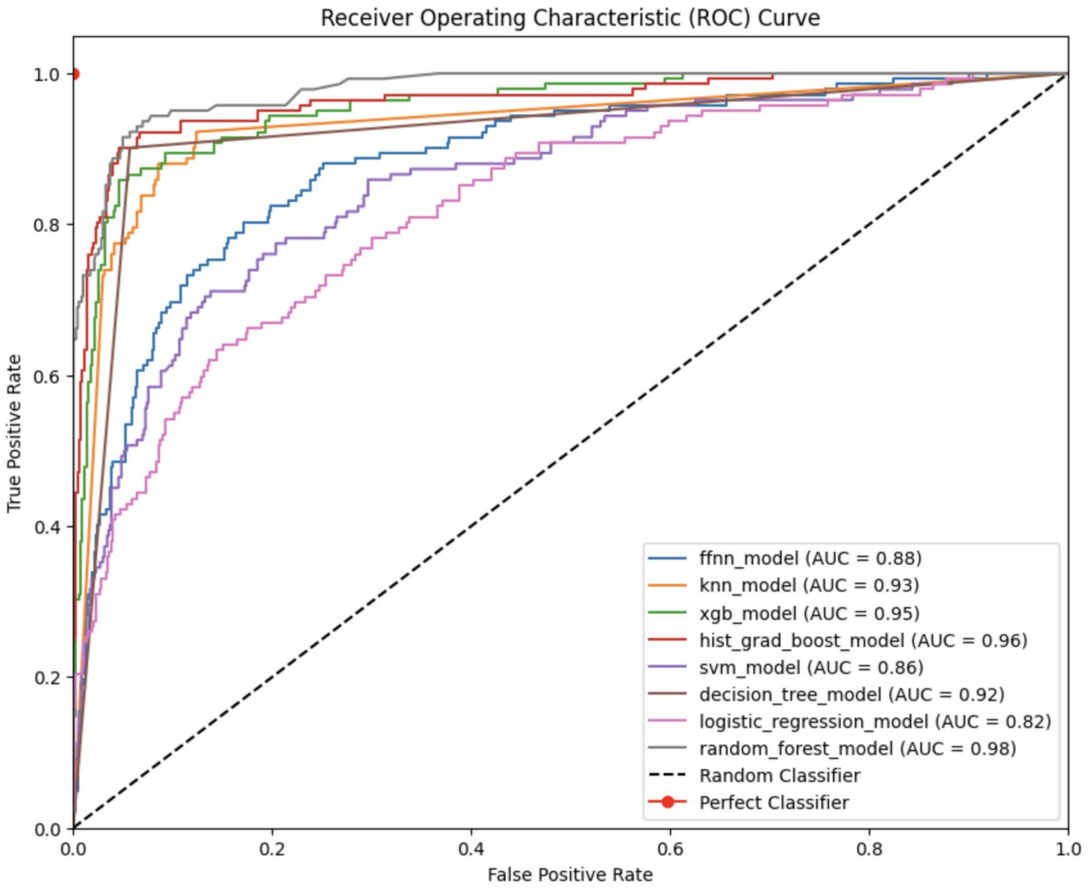
Baseline and Experimentation

Model	**Hyperparameters**	**Training Accuracy**	**Validation Accuracy**	**Improvement over Baseline %**
Baseline: Majority Class Classifier	N/A	0.71	0.71	0.00
Logistic Regression	Sigmoid activation, Cross Entropy Loss, 50 Epochs, Early Stopping	0.83	0.83	15.76
Grid Search Random Forest Classifier	**200 estimators, max depth = 0, max features = sqrt, min split = 2**	**1.00**	**0.95**	**32.51**
HistGradientBoostingClassifier comprehensive grid search	Learning rate = 0.2, max iterations = 300, min samples leaf = 20, l2 reg.	1.00	0.94	32.18
FFNN with Grid Search	2 hidden layers of 32 units, lr = 0.01	0.85	0.87	21.24
Support Vector Machine, grid searched, 5 fold cross validation	C = 10, degree = 3, gamma = auto, kernel = rbf	0.90	0.87	21.40
K-Nearest Neighbors, grid searched, 5 fold cross validation	Manhattan distance, 3 neighbors, p = 1, weights = distance	1.00	0.91	27.87
XGBoost Classifier, grid searched, 5 fold cross validation	Learning rate = 0.2, Max depth = 9, log loss, n_estimators = 150, col sample by tree = 0.7	1.00	0.93	30.69
Decision Tree, grid searched, 5-fold cross-validation	Entropy criteria, no max depth, no max features, min sample split = 2	1.00	0.94	31.02

Churn Prediction - Model Performance



Churn Prediction - Model Performance



Random Forest Model (best model) AUC is 0.98

Customer LFTV

Data Statistics and Preprocessing

Source: Retail Sales and Customer Behavior Analysis

https://www.kaggle.com/datasets/utkalk/large-retail-data-set-for-eda

Key Statistics:

Initial Shape: (1,000,000, 78)
After cleaning and EDA: (500,000, 24)

Feature Engineering to Develop our Ground Truth Customer LFTV:

LFTV = Average Purchase Value x Purchase Frequency x Customer Lifespan (CL)

Customer Lifespan was calculated using conditional logic based on loyalty membership years

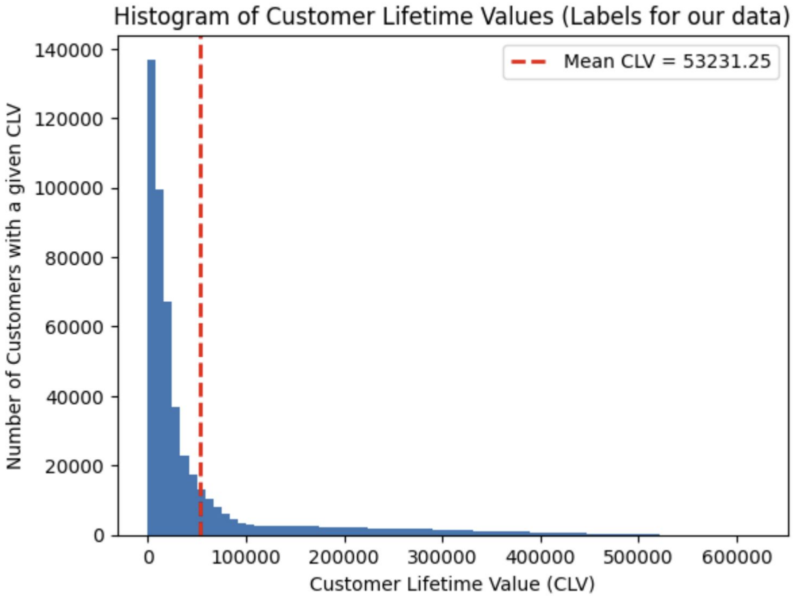
Final LFTV = mean of calculations from APV x PF x CL, and Total sales x CL

LFTV Data Cleaning

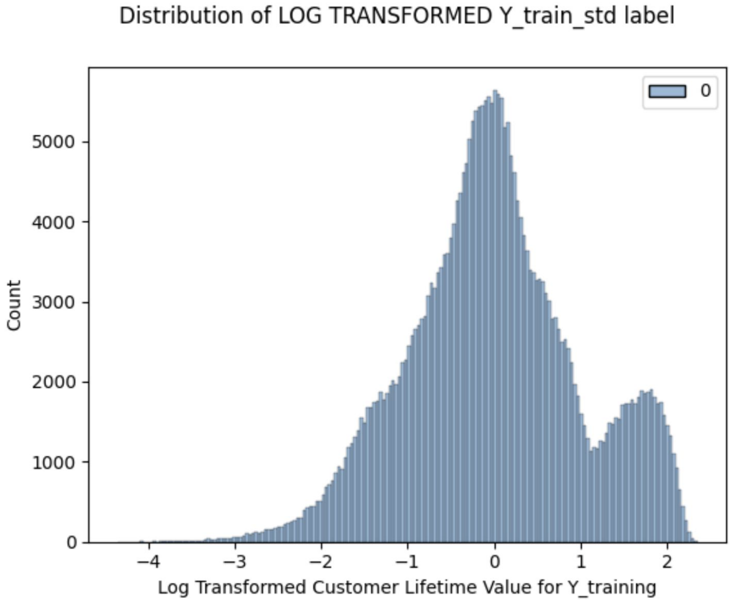
- Add noise-adjusted columns. Drop their 'pure' counterparts
  - Used normal distribution to add noise
  - Drop avg_purchase_value, purchase_frequency, membership_years, total_sales
- One Hot Encode categorical features
  - income_bracket, app_usage, social_media_engagement
- Address skewness, outliers in Y through transformation
  - Log transformation of Y (customer lifetime value)
- Standard scale numeric features

Customer LFTV EDA

Distribution of LFTV Model Target Variable before transformation



Distribution of LFTV Model Target Variable after log transformation



Customer LFTV Experimentation

	Baseline Model: Simple Linear Regression	Feed Forward Neural Network
Hyperparameters	N/A	2 hidden layers with unit sizes 32 and 16, relu activation, adam optimizer, MSE loss function, Early Stopping, 3329 parameters, 100 epochs, batch size of 32
Training RMSE	93.02%	23.00%
Validation RMSE	92.52%	23.07%
Improvement over baseline	N/A	74.9%
Test RMSE	N/A	23.23%

Customer LFTV Experimentation

Model	**Hyperparameters**	**Training RMSE**	**Validation RMSE**
Baseline: Simple Linear Regression with No Feature Selection	N/A	179.01%	178.29%
Simple Linear Regression with Feature Selection	N/A	93.02%	92.52%
Feed Forward Neural Network with No Feature Selection	2 hidden layers, unit sizes 32 and 16, relu activation, adam optimizer, MSE loss function, Early Stopping, 3585 parameters, 50 epochs, batch size of 32	178.73%	178.00%
Feed Forward Neural Network with Feature Selection	**2 hidden layers, unit sizes 32 and 16, relu activation, adam optimizer, MSE loss function, Early Stopping, 3329 parameters, 100 epochs, batch size of 32**	**23.00%**	**23.07%**

Customer Segmentation

Segmentation Data Preprocessing

Same dataset as Customer Lifetime Value, but different feature engineering and selection process, as described below:

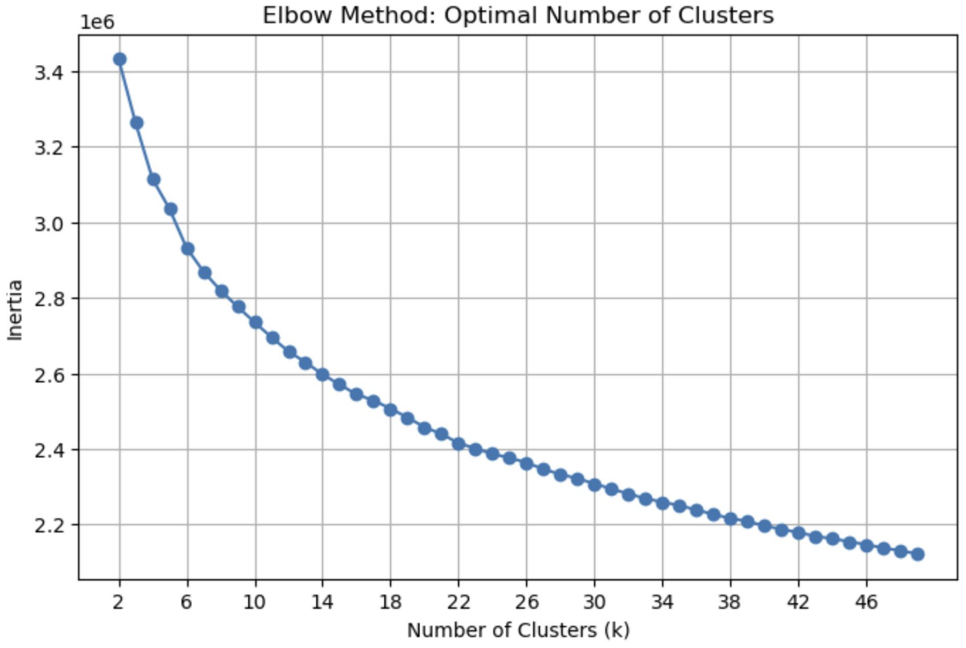
- Created new feature, recency, for days since last transaction
- One Hot Encoded loyalty_program feature (Yes/No)
- Ordinal Encoded the following features:
  - app_usage, social_media_engagement, income_bracket, promotion_effectiveness
- Standard Scale for all numerical features

Column Name	Data Type
recency	int64
frequency	int64
monetary	float64
customer_lifetime_value	float64
customer_lifespan	float64
total_transactions	int64
loyalty_program	object
avg_discount_used	float64
app_usage	object
social_media_engagement	object
income_bracket	object
age	int64
promotion_effectiveness	object
online_purchases	int64
in_store_purchases	int64

Segmentation Experimentation

Initially ran K Means with 5 clusters as a baseline

Used **inertia score** to select the number of clusters via **Elbow Plot**

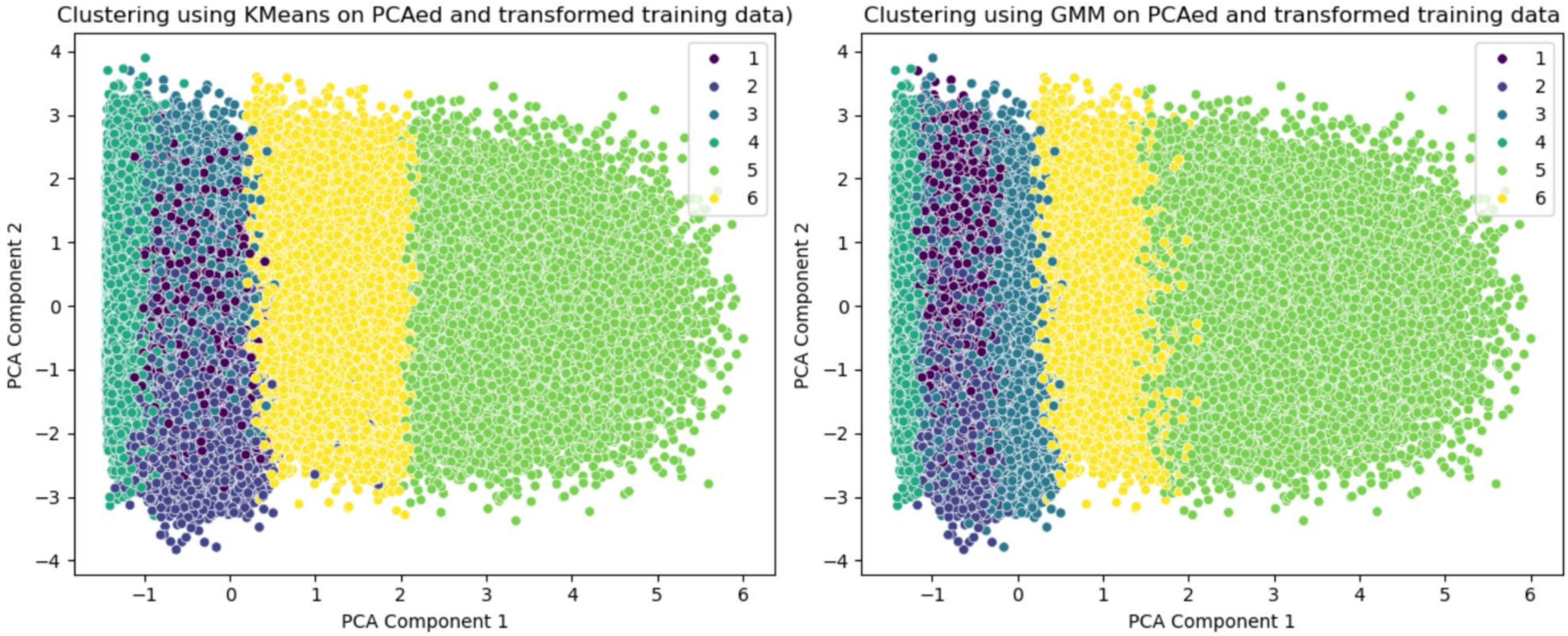


Based on these results, we ran K Means on 6 clusters, which has inertia 2.94. This is 38% higher than lowest inertia (highest accuracy).

To keep number of customer segments meaningful, we accept this accuracy, and chose 6 as an optimal number of clusters.

GMM actually outperformed KMeans

Clusters 1, 2, and 3 that have poor separation in K-Means have better quality cluster separation using GMM



Better machine would run GMM on full data set, w/o PCA. Absent that, we stick with K Means

Silhouette Plot (K Means)

Interpreting the plot

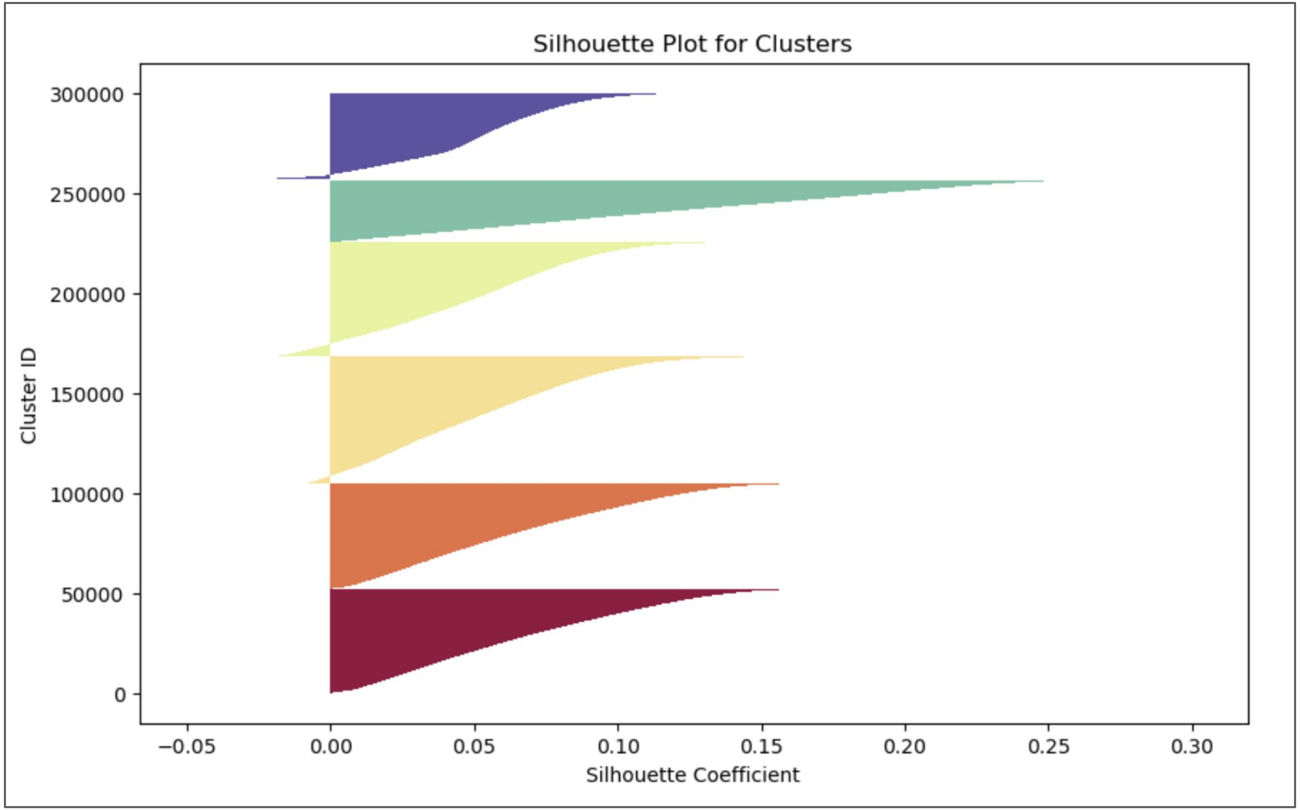
Scores range from -1 to +1

+1: The point is very well clustered, far from neighboring clusters.

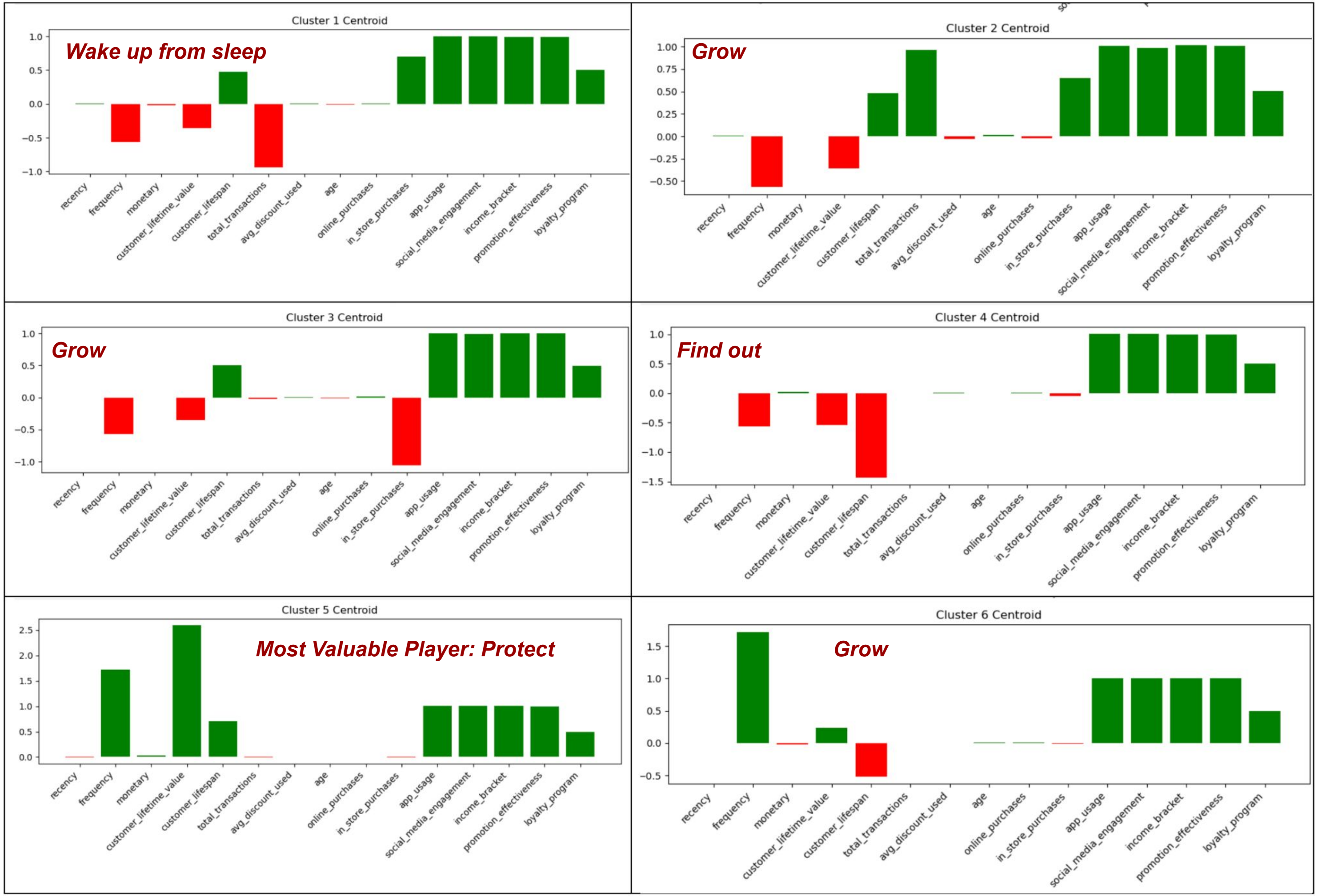
0: The point is on or near the decision boundary between clusters.

-1: The point is likely in the wrong cluster, as it's closer to a neighboring cluster.

As we can see from the plot, most of our points are close to a decision boundary, with only a few likely misclassified.



Customer Segments from K Means



Cluster 1, Segment: **Moderation Molly, Digitally active, Doesn't buy**
Action: Use social media, app to increase online purchases and monetary, frequency values.

Cluster 2, Segment: **High transaction, low frequency buyer.**
Action: Launch promotions to increase frequency (that should drive up monetary scores as customer tends to buy a lot when she makes a purchase).

Cluster 3, Segment: **In-store hating, low lifetime value customer who somehow still sticks around**
Action: Launch promotions (online and digital channels) to increase frequency and monetary scores.

Cluster 4, Segment: **'Mountain to climb' customer segment.**
Most difficult segment: lowest lifespans, low customer lifetime value, low frequency.
Action: Conduct surveys to discover reasons for low traction.

Cluster 5. Segment: **Most Valuable Players Highest Lifetime Value, high frequency customers**
Action: Drive interventions if needed to minimize churn. Launch new campaigns to increase loyalty scores

Cluster 6, Segment: **High frequency, low volume buyers.** Purchases frequently
Action: Use online and digital channels for campaigns to increase retention rates, monetary scores.

Conclusion

Key Results

XXX

Takeaways

XXX

Future Work

XXX

Thank you!