Capstone Project:
E-Commerce Website
Customers Segmentation

Problem Statement

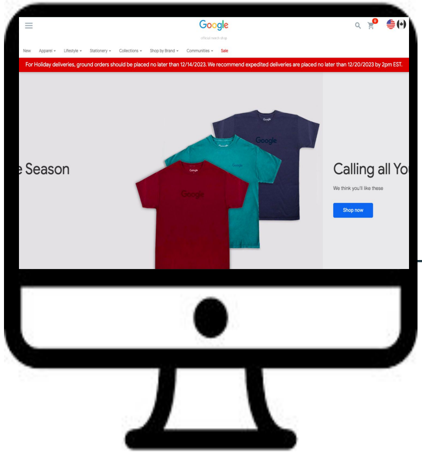
The marketing team of the Google Merchandise website wants to identify different segments from its pool of customer data, understand each segment's behavior, determine the segment that marketing team should invest its marketing expenditure to boost their spending and propose marketing tactics for the chosen segment

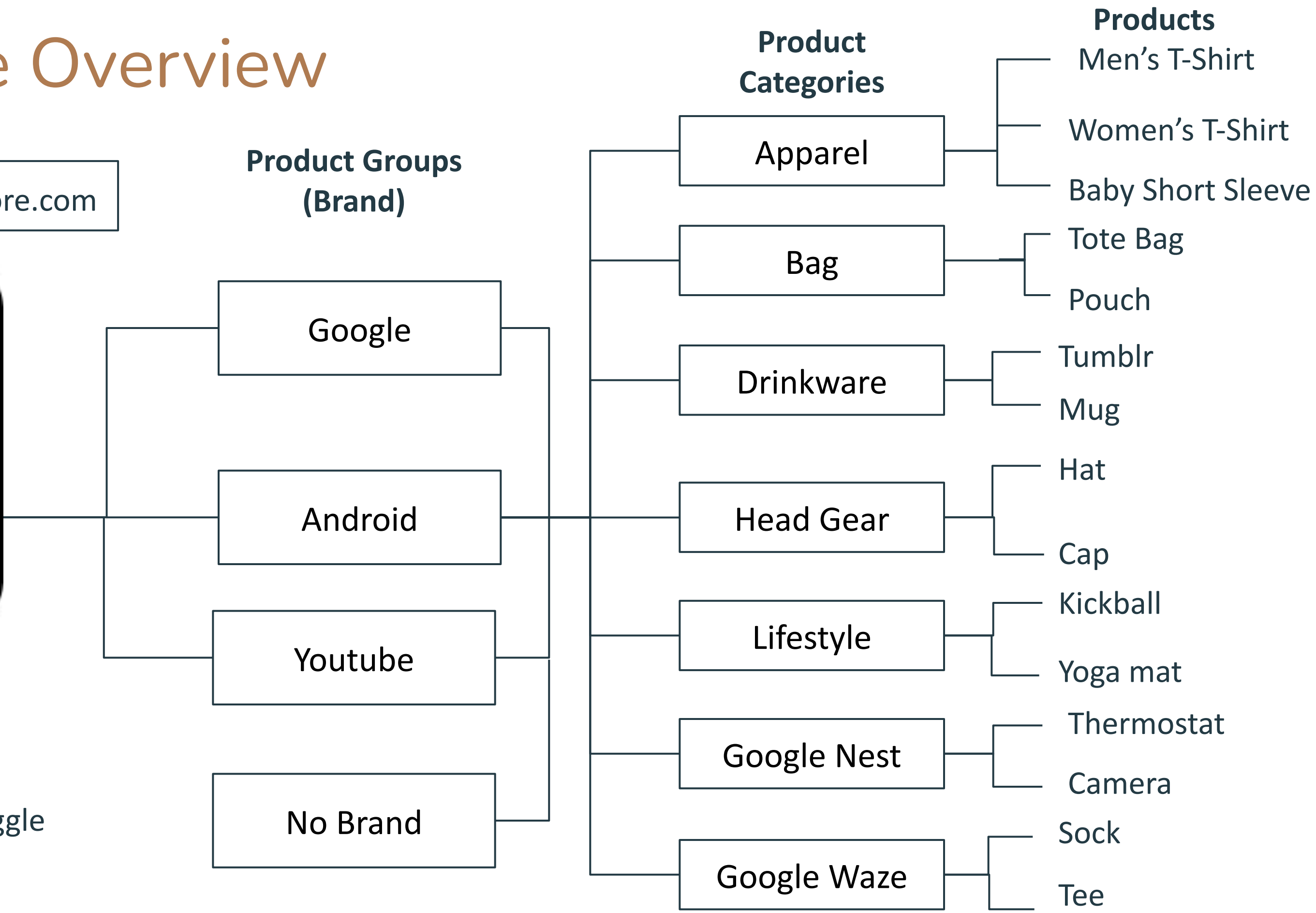
Process:

1. Identify different segments of customers
2. Understand each customer segment behavior
3. Choose a customer segment to invest marketing expenditure
4. Determine marketing tactics for the chosen segment

Website Overview

shop.googlemerchandisestore.com





Data is retrieved from Kaggle

Data Preview

Data Range: 2019-01-01 to 2019-12-31 (364 days)

Coupon	
Month	Discount coupon applied in that month
Product_Category	Product category
Coupon_Code	Coupon code for given category and given month
Discout_pct	Discount percentage for given coupon

Tax	
Product_Category	Product category
GST	Percentage of GST

Products	
Products_SKU	Product unique ID
Product_Category	Product category
Product_Description	Product name

Sales	
CustomerID	Customer unique ID
Transaction_ID	Transaction Unique ID
Transaction_Date	Date of Transaction
Product_SKU	Product unique ID
Product_Description	Product name
Product_Category	Product category
Quantity	Number of items ordered
Avg_Price	Price per one quantity
Delivery_Charges	Charges for delivery
Coupon_Status	Any discount coupon

Customer	
CustomerID	Customer unique ID
Gender	Gender of customer
Location	Location of customer
Tenure_Months	Tenure in months

Marketing Expenditure	
Date	Date
Offline_Marketing_Expense	Marketing spend on offline channels like TV, Radio, Newspapers
Online_Marketing_Expense	Marketing spend on online channels like Google keywords, Facebook

Data Preparation: Customer Analysis and Product Analysis

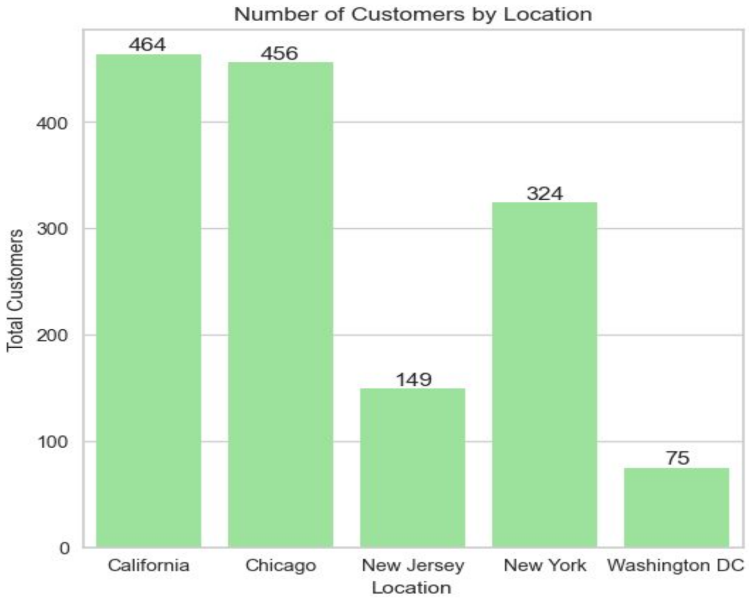
Customer Centric

Customer_Analysis	
CustomerID	Customer unique ID
Total_Spending	Total spending of customer
Delivery_Charges	Total delivery charges of customer
Num_Transactions	Total number of transactions
Total_Quantity	Total quantities
Location	Location of customer
Gender	Gender of customer
Tenure_Months	Tenure in months
Used_Coupon_Count	Total number of coupons used
Not_Use_Coupon_Count	Total number of coupons not used
Clicked_Coupon_Count	Total number of coupon clicked
Revenue	Total revenue

Product_Analysis	
CustomerID	Customer unique ID
Purchased_Products	List of total products purchased
Products_SKUS	Product unique ID
Product_Categories	Product category
Product_Group	Product Group

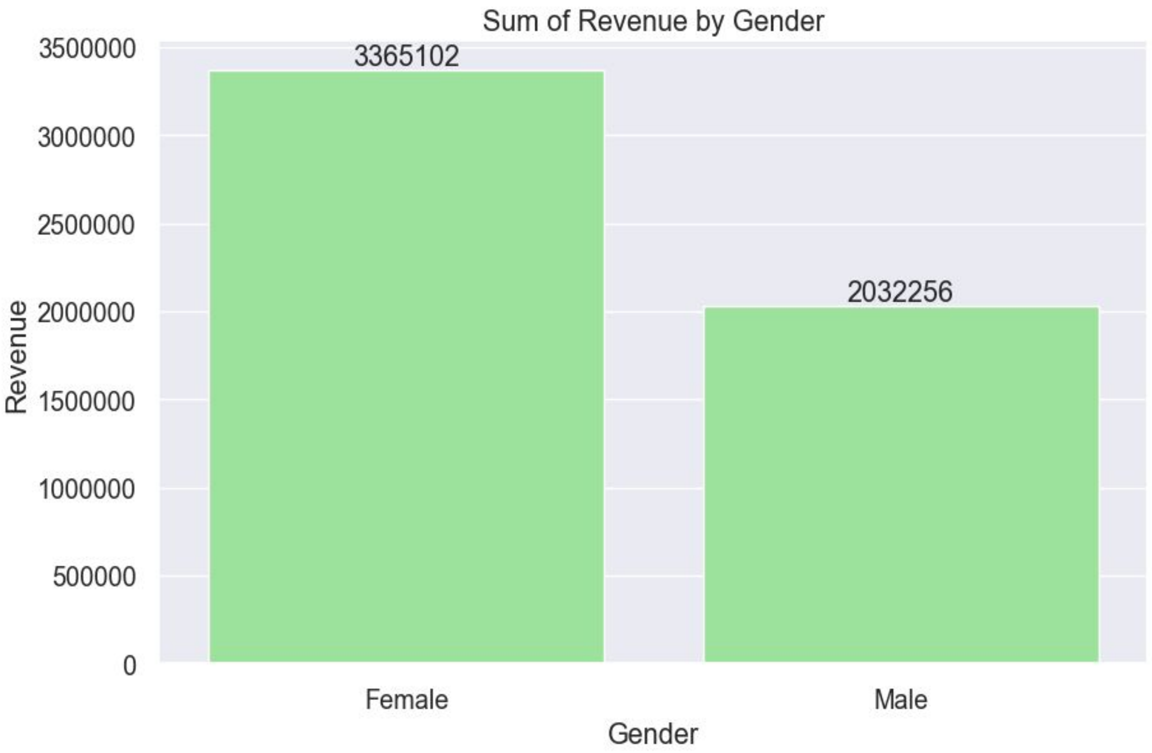
Exploratory Data Analysis

Revenue and Number of Customers per Location



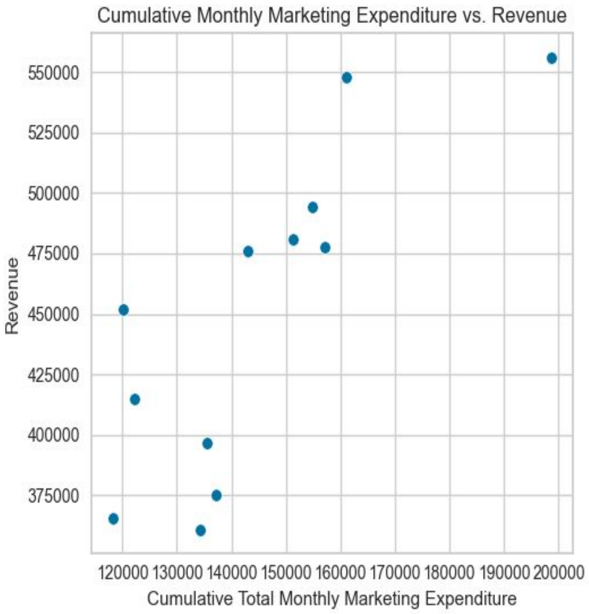
- Chicago, California, and New York are top 3 locations with highest revenue and number of customers
- New Jersey and Washington DC acquire lowest revenue and number of customers

Gender vs. Revenue



- Female spends higher than male

Marketing Expenditure vs. Revenue



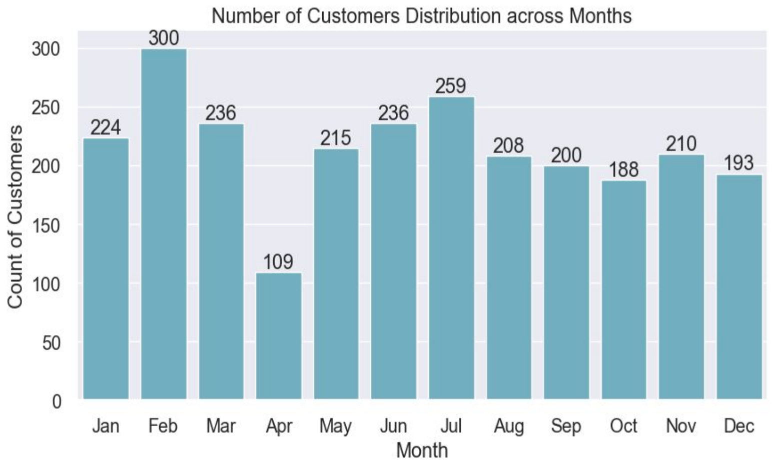
Correlation: 0.796

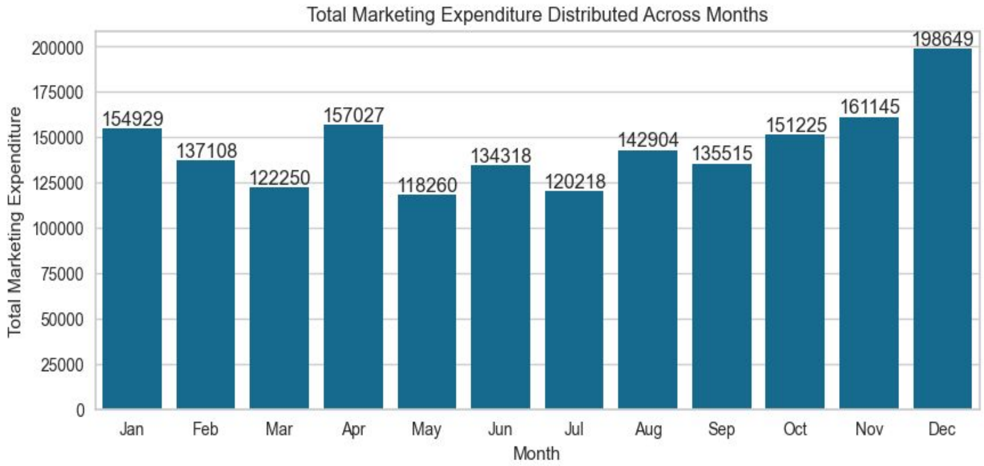
Correlation: 0.811

Correlation: 0.757

- High marketing expenditure both online and offline reflects high revenue obtained

Marketing Expenditure vs. Customers Distribution

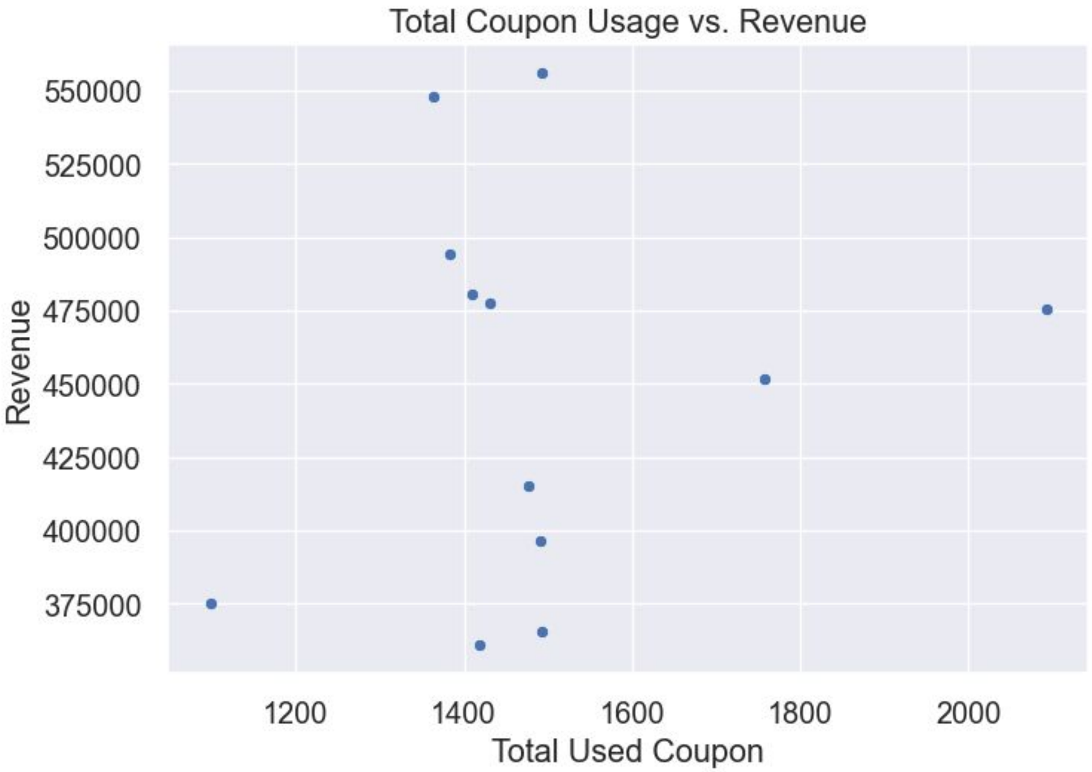




- Top 2 months with highest customers: February and July
- April has lowest customers

- Top 2 months with highest marketing expenditure: November and December

Total Coupon Usage vs. Revenue



Correlation: 0.175

High coupons used among customers did not generate high revenue

Data Analysis Conclusion

- Allocated higher marketing expenditure to target low revenue and customers factors:
  - Location: New Jersey and Washington DC
  - Gender: Male
  - Months: April, November, and December

  Increase purchasing
- High investment in marketing yields higher revenue
- Releasing more coupons do not generate higher revenue

Feature Engineering

RFM Analysis: What is it and Why it is needed

Definition of RFM analysis

- **Recency** (Days Since Last Purchase): The number of days between the customers last purchase and their first purchase. How many days does it take for customers to make the next purchase
- **Frequency**: How many days or how often during the observed period does a customer made purchases
  - Calculated based on the number of days customers made purchase
- **Monetary Value**: Total revenue gained from the customer during their tenure

Why RFM analysis is needed

- Obtained additional relevant features such as frequency and Days Since Last Purchase that can be included in the modeled data.
- Better understanding of customer purchasing behavior and future purchasing behavior, can lead to better segmentation of customers

Feature Engineering using RFM Analysis Procedure

Generate customer-centric RFM table (Days since last purchase, Frequency, Monetary Value)

Implement Beta-Geometric then Gamma-Gamma Model on the RFM data

Beta-Geometric: predict CLV, analyze purchasing frequency, and future purchase prediction

Gamma-Gamma: predict future monetary value

RFM Analysis DataFrame

Obtained each customer:

1. Days since last purchase
2. Tenure Days
3. Purchased frequency
4. Monetary Value
5. Predicted Purchases
6. Predicted Revenue
7. Customer LifeTime Value (CLV)

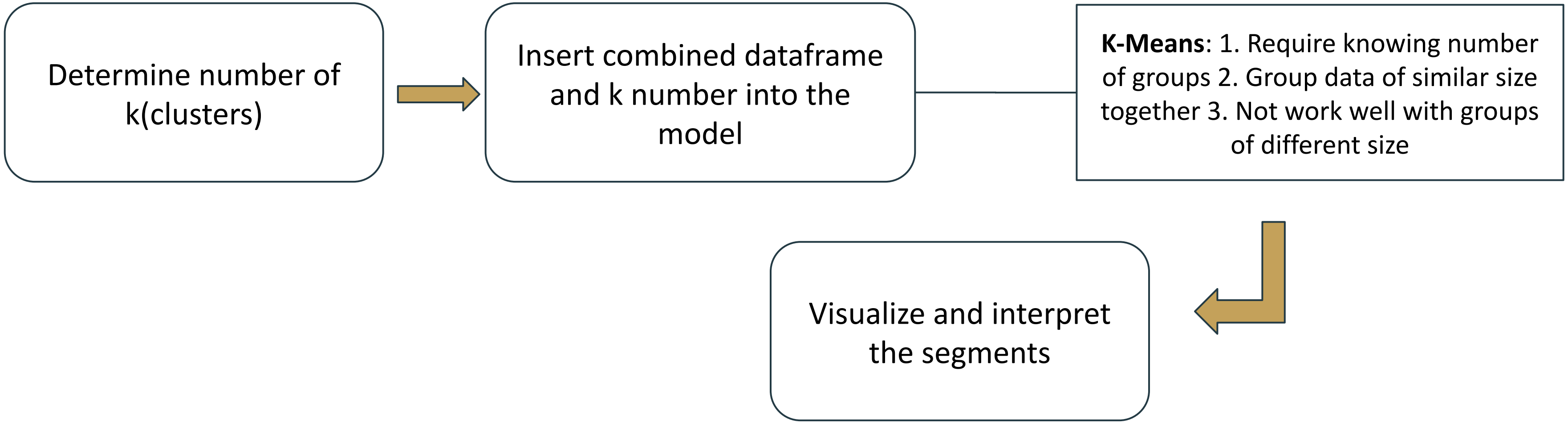
Combined RFM DataFrame with Customer_Analysis DataFrame

RFM Analysis

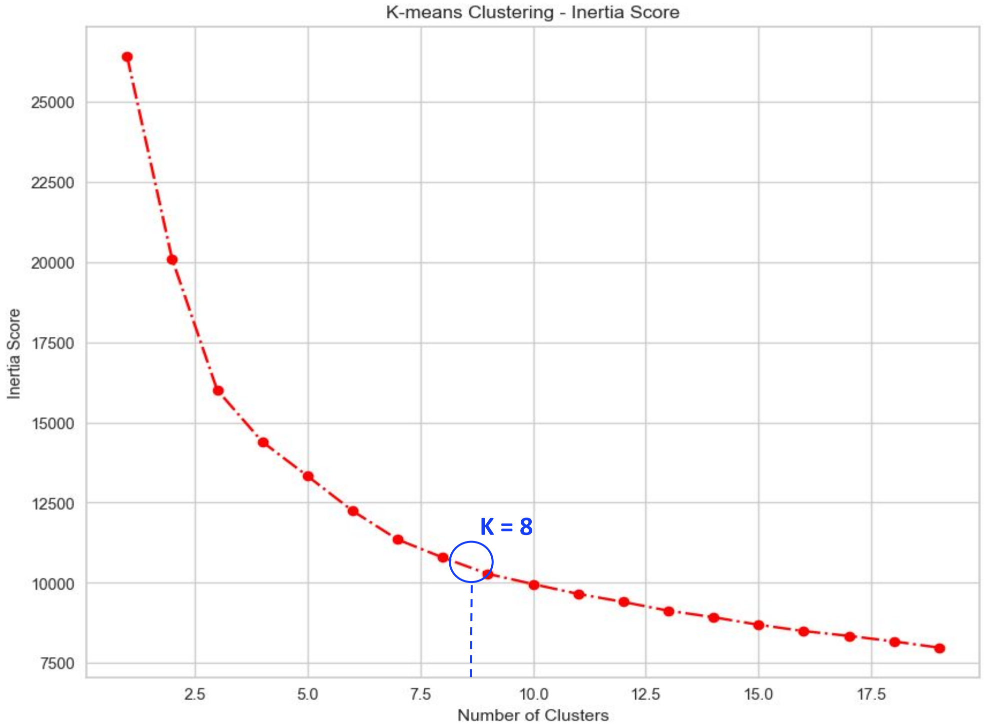
RFM Analysis		
Feature	**Definition**	**Calculation**
CustomerID	Unique customer ID	
Days_Since_Last_Purchase	Number of days since customer last purchase	Last Purchase Date - Preceding Purchase Date
Tenure_Days	Number of days customer have been with the store	
Purchased_Frequency	Number days customer made purchase	
Monetary_Value	Revenue gained from customer during their tenure	
Predicted_Purchases	Expected number of future purchases of the customer	recency (Days_Since_Last_Purchase) and frequency (historical transaction frequency) to estimate future purchase behavior.
Predicted_Revenue	Expected future revenue the customer is expected to generate	Predicted Purchases x Predicted Average Transaction Value
Customer LifeTime Value (CLV)	Total value a customer is expected to generate over their entire relationship with the store	Expected Number of Transactions×Predicted Average Transaction Value

Modeling: Unsupervised Learning Clustering

Unsupervised Clustering Execution Process



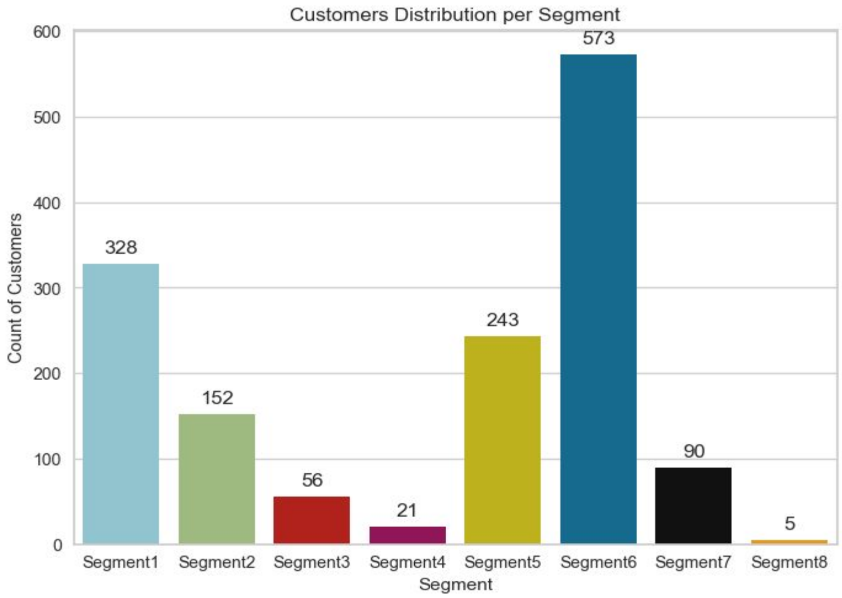
K-Means Clustering: Number of Clusters Evaluation



- Inertia Score Evaluation (Elbow method):
  - How compact together the data points are within each cluster
  - Elbow method: choose K when the decrease of Inertia score flattens out
  - Optimal number of clusters = 8

Label Outcome Evaluation

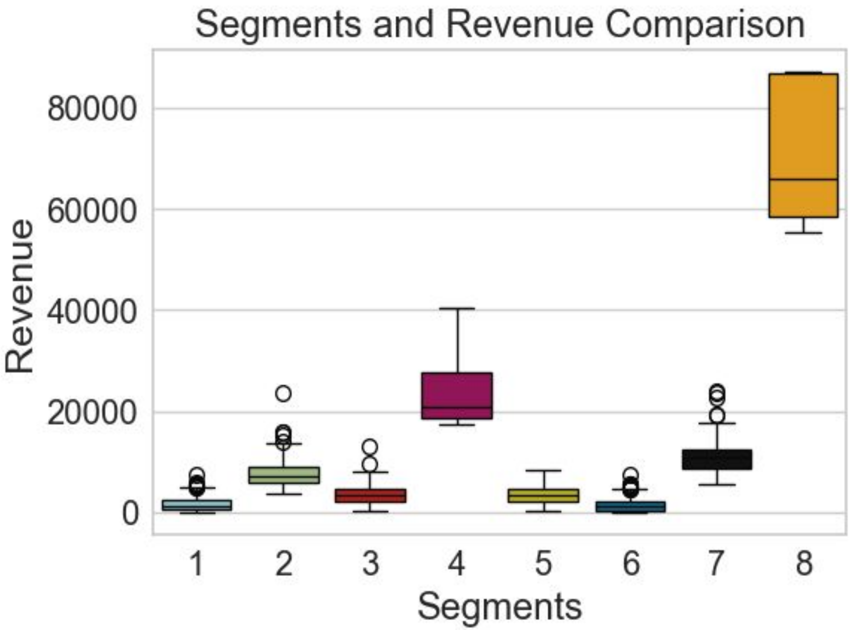
K-Means Clustering



- More customers distributed in Segment1, Segment2, Segment5, and Segment6
- Targeting these segments maximize potential return of marketing investment
    - Higher market reach and higher revenue capturing

Data Distribution: Proportionate data distribution

Segments and Revenue Comparison

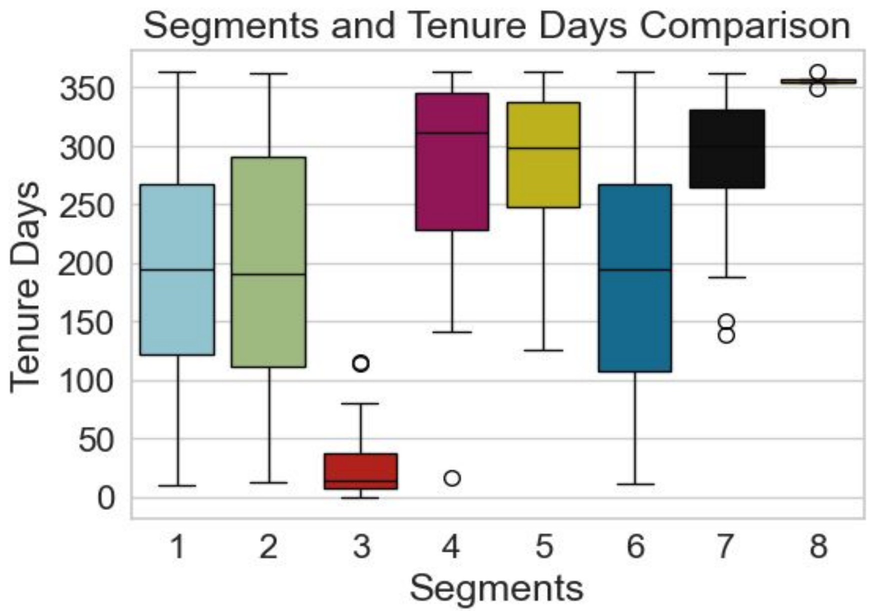


Mean Revenue by Segment

Segment	Revenue
Segment6	1382
Segment1	1573
Segment5	3475
Segment3	3549
Segment2	7773
Segment7	11211
Segment4	23863
Segment8	70779

Segment 6 and Segment 1 generate lowest revenue.

Segments and Tenure Days Comparison

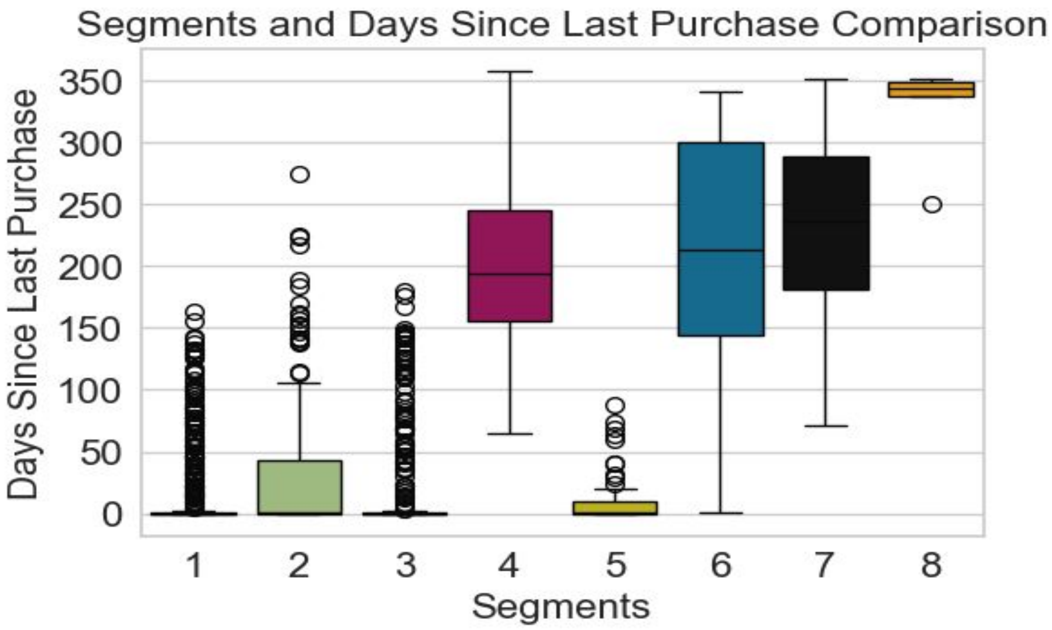


Mean Tenure Days by Segment

Segment	Tenure_Days
Segment3	26
Segment6	188
Segment1	192
Segment2	198
Segment4	280
Segment5	287
Segment7	293
Segment8	355

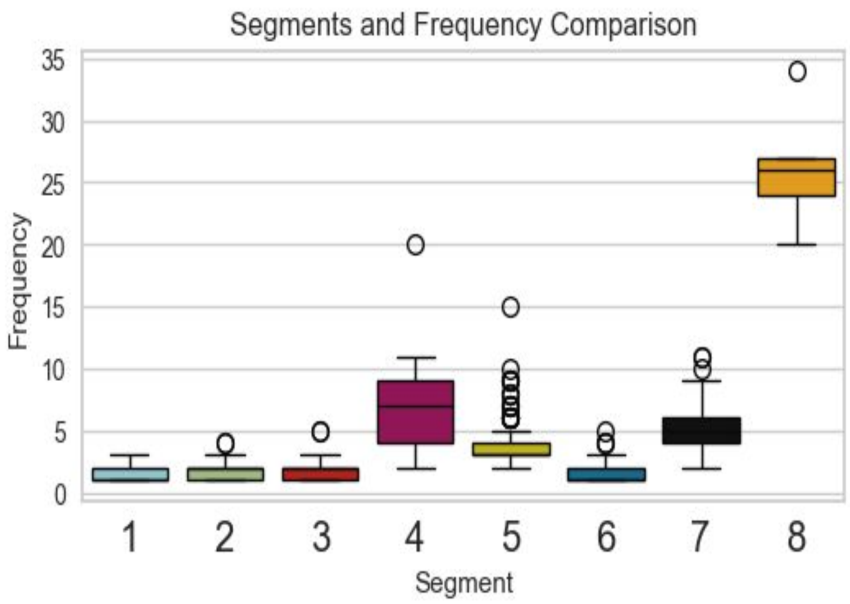
Segment1, 3, and 6 tenure days (in business with the store) are the lowest.

Segments and Days Since Last Purchase Comparison



- Days since last purchase = 0 in Segment 1, 2,3 and 5 represent customers that purchase only once
- Segment 6 has highest average duration between 2 purchases

Segments and Frequency Comparison

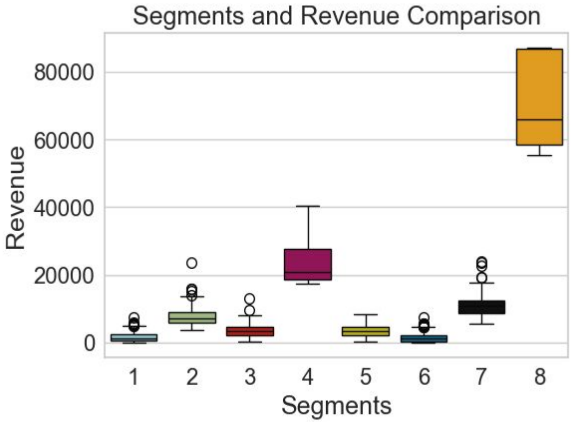


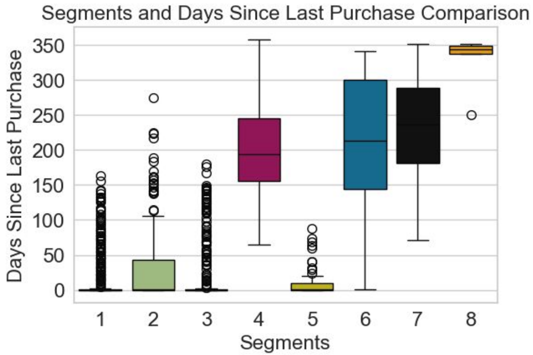
Mean Frequency by Segment

	Segment	frequency
5	Segment6	1.301920
0	Segment1	1.365854
1	Segment2	1.750000
2	Segment3	1.857143
4	Segment5	3.736626
6	Segment7	5.055556
3	Segment4	7.142857
7	Segment8	26.200000

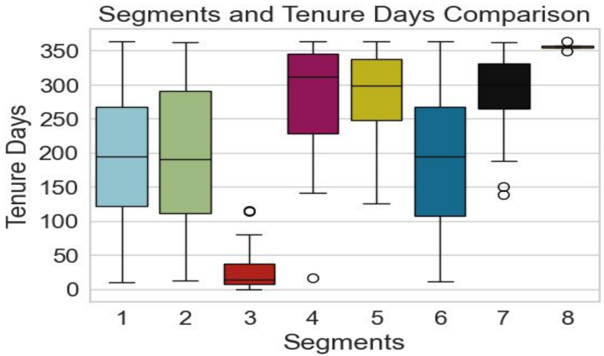
Segment 1 and Segment 6 are the lowest frequently purchase groups

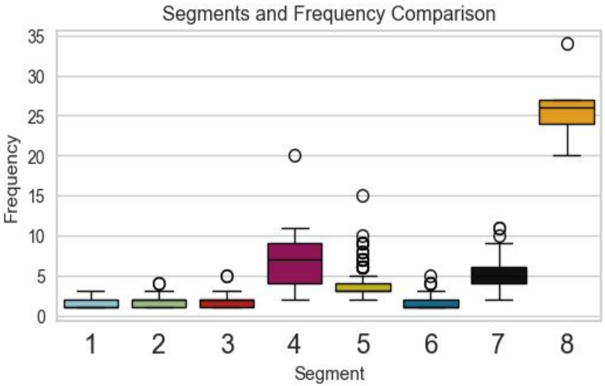
K-Means Clustering Segment Evaluation





- **Focus Low Valued Segments**
  Segment1 and Segment6:
  - 1. Lowest revenue
  - 2. Low tenure days
  - 3. Majority made purchase only once
  - 4. Low purchase frequency

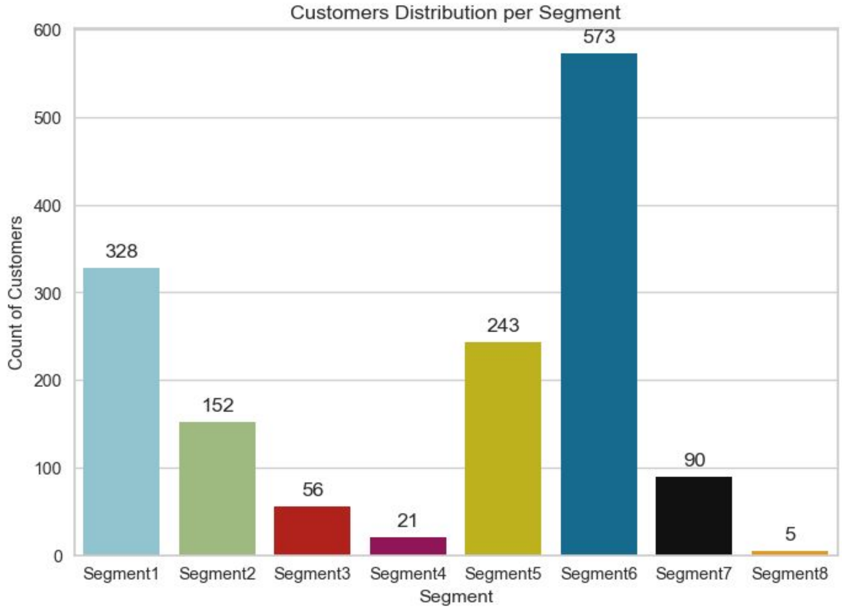




Recommendation

Segment to Focus Marketing Expenditure

- Among 8 segments : Target Segment 1 and Segment 6



Segment 1 and Segment 6

- **Low-valued segments**
- Majority of customers resided in Chicago, California, and New York
- 60% of customers are female
- Top purchased product group is Google
- Top 5 product categories: Office, Apparel, Drinkware, Lifestyle, and Nest
- Top purchased products: Maze Pen, Google 22 oz Water Bottle, Google Sunglasses, Sport Bag, Ballpoint LED Light Pen, Google Kick Ball, Foam Can and Bottle Cooler

Marketing Strategies for Target Segments

- Targeted campaign email marketing - email marketing for specific audiences
  - Specified the customers emails as Segment 1 and Segment 6
  - Email content:
    - Re-engage customers with their top product categories: Office, Drinkware, Apparel and top product group: Google
    - Promoting unpopular product categories such as Accessories, Google Waze, Gift Cards and unpopular product group: Youtube, using special promotions such as price reduction
    - Bundle deals
  - Increase email marketing sent out in November and December for Black Friday and Christmas event, and April as the lowest number of customers month
  - Allocate higher email marketing resource to specific demographics to increase awarenesses and purchases:
    - Gender: Male
    - Location: New Jersey and Washington DC

Limitations / Further Improvement

Limitation

- Data from Kaggle might not be valid
- Limited relevant features of customers and limited data range: only 1 year
- Undefined company’s resources to determine the potential return of marketing investment

Further Improvement

- Apply model on real-world data
- Product Recommendation: recommending by utilizing product name similarities using cosine similarity score such as purchasing Android BTTF Cosmos Graphic Tee will recommend Android Women's Long Sleeve Blended Cardigan Grey
- Product Bundle: bundle deals of products frequently purchased together such as Nest Cam Outdoor Security Camera and Nest Cam Indoor Security Camera

Thank you