

OPTIMIZING HOME DELIVERY IN SMALL GROCERY STORES:

A Data-Driven Strategy for Customer Segmentation

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Introduction

Context:

- Small grocery stores face competition from supermarkets and online platforms.
- Customer retention and personalized marketing are crucial for survival.

Motivation:

- Growing up in a family running a small grocery store, I saw the challenges firsthand.
- This inspired me to explore affordable, datadriven solutions for customer engagement.



Research Questions



1. How can customer segmentation improve targeted marketing?



2. How can churn (Risk of losing a customer) prediction help small grocery stores?



3. How can RFM(Recency, Frequency, Monetary) analysis be used to segment customers?



4. How accurately can machine learning models predict churn?



5. What insights can be derived from clustering, and how can they improve marketing strategies?





Keywords

- Customer Segmentation
- Targeted Marketing
- Churn Prediction
- RFM (Recency, Frequency, Monetary) Analysis
- K-Means Clustering
- Machine Learning
- Small Grocery Stores
- Home Delivery

Methodology

Data Used:

• 541,909 transactional entries (CustomerID, InvoiceDate, Stockcode, Quantity, UnitPrice, etc.).

Techniques:

- RFM Analysis: To quantify customer behavior.
- **K-Means Clustering**: To group customers into distinct segments.
- Churn Prediction Models: Logistic Regression, Random Forest, and Gradient Boosting.

Churn =0- Minimal risk of losing the customer.

Churn =1- Potential risk of losing the customer.

Steps:

- Data cleaning and preparation.
- RFM score computation.
- · Clustering and churn modeling.



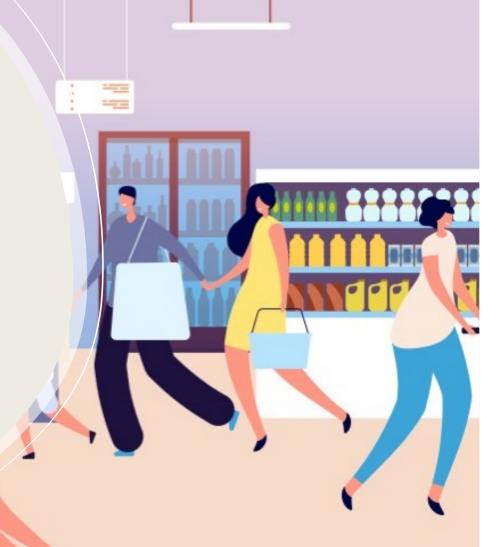
Results & Analysis

RFM Insights:

- Loyal customers had low Recency and high Frequency/Monetary values.
- Disengaged customers had high Recency, requiring re-engagement.

Clustering:

- Four clusters identified (0-Loyal, 1- Moderate,
- 2-Occasional, and 3-At-Risk customers).
- Silhouette Score: 0.601.



Churn Prediction:

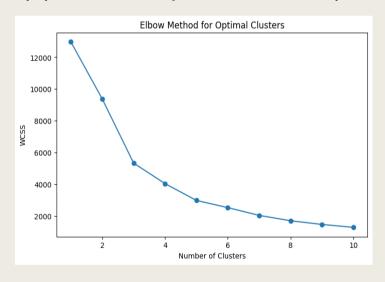
- All models achieved 100% accuracy.
- Recency was the most critical feature for predicting churn.

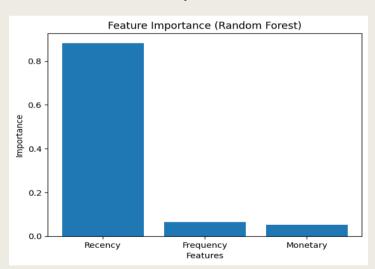
CustomerID	Recency	Frequency	Monetary	Churn
12347.0	1	182	4310.00	0
12348.0	74	27	1595.64	0
12349.0	18	72	1457.55	0
12350.0	309	17	334.40	1
12352.0	35	89	1545.41	0

Visuals

(a) Elbow Method graph for determining the number of clusters.

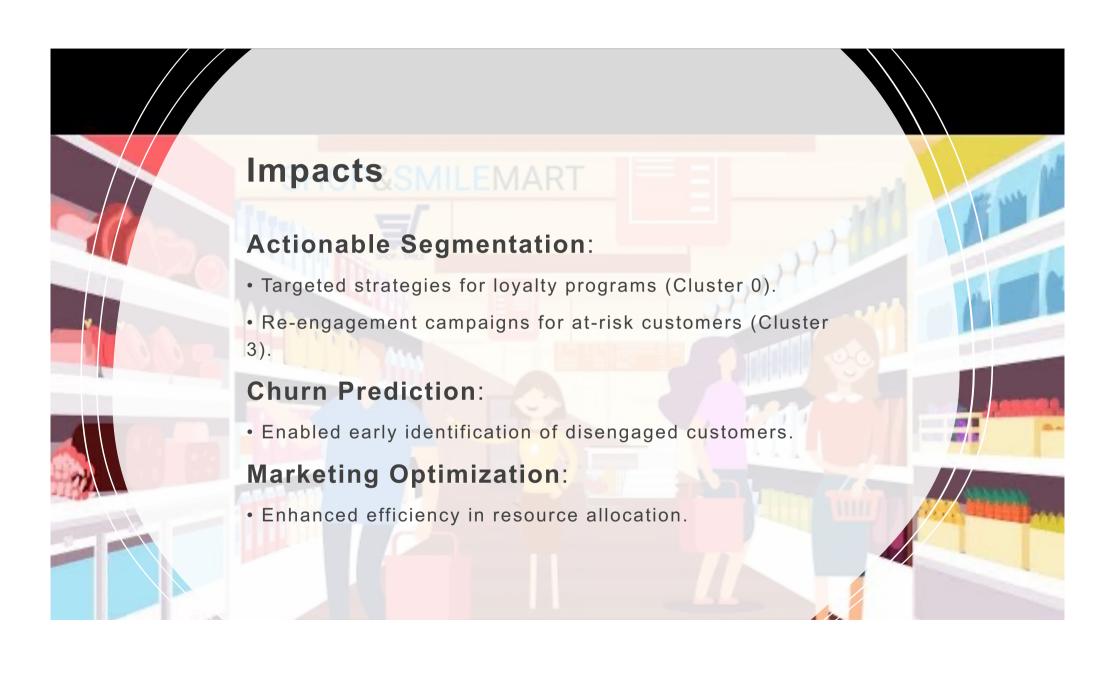
(b) Feature Importance chart (Random Forest model).





(a)

(b)



Recommendations



• IMPLEMENT RFM-BASED SEGMENTATION FOR PERSONALIZED CAMPAIGNS.



• FOCUS ON LOYALTY PROGRAMS FOR HIGH-VALUE CUSTOMERS.



USE CHURN
 PREDICTION TO
 GUIDE RE ENGAGEMENT
 STRATEGIES.



• INTEGRATE
DEMOGRAPHIC
DATA TO REFINE
CUSTOMER
INSIGHTS.



APPLY REAL-TIME
 ANALYTICS FOR
 DYNAMIC
 SEGMENTATION.

Limitations

Data Constraints:

 Transactional data only; demographic or behavioral data was not included.

Scalability:

 Findings are specific to a single grocery store context.

Generalizability:

• Results may vary for other geographic locations or larger datasets.





Integration of Real-Time Analytics:

• Update RFM metrics dynamically for responsive marketing.

Scaling:

• Test on larger datasets and multi-store environments.

Incorporating Additional Data:

• Demographics, purchase preferences, and seasonal trends.

Recommendation Systems:

Build personalized product recommendations for customers.

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