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The Customer Loyalty Price Sensitivity Correlation: An Analysis of Frequent Buyer vs Single Purchase Behaviour

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ABSTRACT: This paper presents an analytical study of the relationship between customer loyalty and price sensitivity in a retail transaction environment. A Partial Least Squares Discriminant Analysis (PLS-DA) model is employed to classify customers into frequent shoppers and single-purchase buyers. Feature engineering techniques are used to derive indicators such as price variance, discount dependence, and elasticity score. Experimental results demonstrate that machine learning-based segmentation effectively distinguishes loyalty-driven customers from price-sensitive consumers, providing actionable insights for data-driven retail pricing and promotion strategies.

KEYWORDS: Customer Loyalty, Price Sensitivity, PLS-DA, Retail Analytics, Python.

I. INTRODUCTION

In the competitive retail sector, understanding the behavioural relationship between pricing strategies and customer loyalty is critical for sustainable revenue growth. Customers often exhibit varying degrees of price sensitivity, influencing purchase frequency and brand commitment. This study aims to analyse and classify customer behaviour by distinguishing loyalty-driven frequent shoppers from price-driven single-purchase buyers using data analytics and machine learning techniques.

II. DATASET DESCRIPTION

The dataset used in this study consists of structured retail transaction records containing purchase values, discount usage, transaction frequency, and pricing information for individual customers. The data was pre-processed to remove inconsistencies and normalized to ensure reliable feature extraction for model training and evaluation.

III. METHODOLOGY

Partial Least Squares Discriminant Analysis (PLS-DA) was employed to maximize class separation between frequent shoppers and single-purchase customers. The model was selected due to its robustness in handling multicollinearity among input variables and its interpretability compared to traditional classification techniques.

3.1 Price Variance

Price Variance represents the standard deviation of product prices paid by an individual customer across transactions. Higher variance indicates inconsistent pricing behaviour, often associated with increased price sensitivity.

3.2 Discount Dependence

Discount Dependence measures the proportion of discounts utilized relative to total customer spending. A higher value reflects stronger reliance on promotional pricing and is indicative of single-purchase or deal-driven behaviour.

3.3 Elasticity Score

Elasticity Score serves as a proxy for purchase frequency in response to price variation. It captures behavioural responsiveness to price changes and helps distinguish loyalty-driven customers from price-sensitive buyers.

IV. RESULTS AND DISCUSSION

The PLS-DA model effectively classified customers based on their purchasing behaviour. Discount dependence emerged as the strongest indicator of single-purchase behaviour, while lower price variance correlated with higher customer loyalty. These findings confirm the model’s capability to support data-driven decision-making in retail environments.

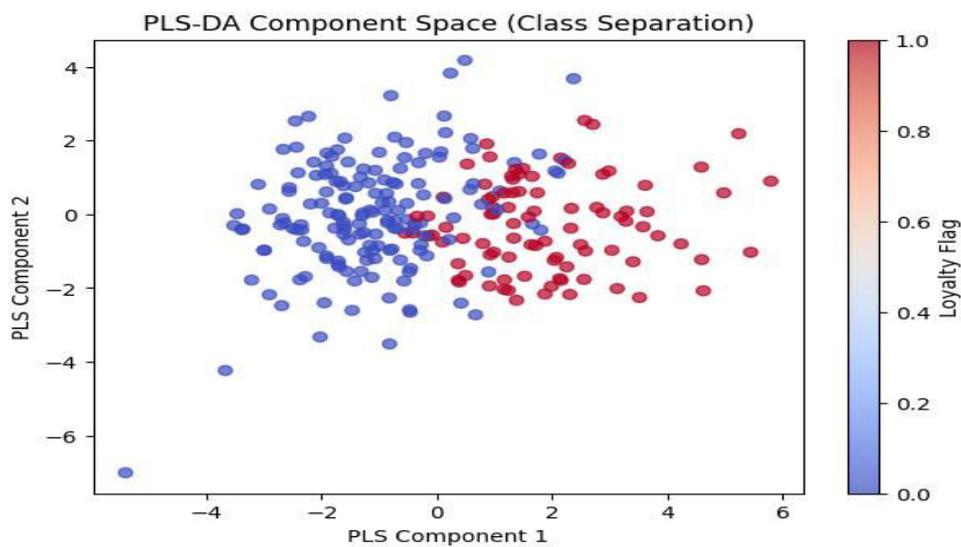


Fig. 1 Scatter plot

Fig. 1 explanation

The figure illustrates the PLS-DA component space showing class separation between frequent shoppers and single-purchase customers. The first PLS component provides clear discrimination between the two classes, indicating strong explanatory power of price-sensitivity features. Limited overlap between clusters suggests effective class separation, while minor intersections reflect borderline behavioural patterns. Overall, the visualization confirms the suitability of PLS-DA for customer loyalty segmentation.

	Precision	Recall	F1-score	Support
0	0.92	0.96	0.94	161
1	0.93	0.85	0.89	89
Accuracy			0.92	250
Macro avg	0.92	0.92	0.92	250
Weighted avg	0.92	0.92	0.92	250

Table.1 metrics

Table 1 summary:

The evaluation metrics of the classification model on the test dataset. An overall accuracy of 92% indicates strong generalization performance. The higher recall for Class 0 (0.96) reflects the model’s effectiveness in capturing frequent shopper behaviour, while the precision of 0.93 for Class 1 indicates low false-positive rates for single-purchase customers. The balanced macro-average scores demonstrate robustness across classes despite class imbalance. Consistent weighted averages further confirm stable predictive performance.

V. CONCLUSION

This study confirms that price sensitivity plays a significant role in shaping customer loyalty patterns. The proposed PLS-DA-based framework successfully segments customers and can be extended to real-time pricing systems, personalized promotions, and intelligent recommendation engines in modern retail applications.

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