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Enhancing Customer Profiling with RFM and CLV: A K-Means and XGBoost Approach

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Contents

1 Abstract

Effective marketing tactics in today's fiercely competitive corporate environment depend on the capacity to comprehend and forecast consumer behavior. This study integrates Recency, Frequency, and Monetary (RFM) analysis with Customer Lifetime Value (CLV) modeling to give a comprehensive framework for customer profiling. The research endeavors to improve the precision of consumer segmentation and the customization of marketing campaigns through the utilization of cutting-edge machine learning methodologies, including XGBoost and K-Means clustering. Utilizing transaction data from a UK-based online store, the study highlights the advantages of merging short- and long-term client indicators. The results show how this integrated strategy can more successfully manage resources, optimize retention efforts, and discover high-value consumers. The findings provide useful information for companies trying to better understand their customers and predict behavior, leading to more targeted and effective marketing campaigns.

2 Introduction

Two essential components of contemporary marketing strategies are lifetime value projection and customer segmentation. Big data and machine learning have given firms access to customer data that was previously unheard of, allowing for more targeted and dynamic marketing campaigns. But conventional approaches frequently fail to provide a complete picture of the client. RFM analysis provides insightful information by looking at prior purchase patterns, however it just looks at the present and doesn't look forward. On the other hand, while CLV offers a long-term evaluation of customer value, it might not account for recent alterations in consumer behavior. In order to close the gap, this study combines RFM and CLV analysis and makes use of cutting-edge machine learning techniques to create a solid foundation for customer profiling. This approach is unusual because it can integrate short-term behavioral observations with long-term value estimates, providing a more complete customer picture. This research attempts to increase the accuracy of client segmentation and the efficacy of marketing tactics by utilizing XGBoost to forecast future CLV and K-Means clustering to segment clients based on RFM scores. The study demonstrates how this integrated strategy offers greater insights into customer retention and personalized marketing initiatives in addition to making it easier to identify high-value consumers. This approach's techniques, difficulties, and results are described, emphasizing how it might revolutionize how companies see and interact with their clientele in the data-driven market of today.

3 Literature Review

3.1 Customer Lifetime Value (CLV)

Customer Lifetime Value (CLV) is a metric used in marketing and business strategy to determine the total value a customer brings to the company through their entire relationship with its products. The calculation of CLV includes factors such as average order value, purchase frequency, and customer churn rate to estimate the total revenue a customer generates for a business. Analyzing CLV can provide insights into the impact of customer experience strategies on long-term customer loyalty and behavior [16]. By comparing the CLV of customers in various retail environments, businesses can gain valuable insights into the effectiveness of their store redesign efforts in enhancing the customer experience and generating lasting value [17]. Additionally, CLV can guide marketing decisions by evaluating their return on investment [11].

3.2 Customer Segmentation

Customer segmentation is a strategic method of categorizing customers into groups based on shared characteristics or behaviors [7]. Customer segmentation has virtually unlimited potential as a tool that can guide firms toward more effective ways to market products and develop new ones [14]. By utilizing various client attributes, organizations can tailor marketing strategies, forecast trends, develop product plans, design campaigns, and offer relevant items [15]. Customer segmentation not only focuses on improving customer satisfaction and loyalty but also maximizes efficiency in resource allocation.

3.3 Machine Learning

The progress of machine learning has been fueled by the emergence of new learning algorithms and theoretical frameworks, along with the continuous expansion of online data availability and decreasing costs of computation [8]. Data-intensive machine-learning methods have been widely used in fields such as science, technology, and business, leading to a shift towards evidence-based decision-making in areas like healthcare, manufacturing, education, financial modeling, policing, and marketing [10].

3.4 Clustering

Clustering is a technique used in data analysis and machine learning that involves grouping a set of objects or data points into clusters where objects in the same cluster are more similar to each other. It is used in customer segmentation, image analysis, and pattern recognition. Clusterwise regression provides a way to find group-specific models. In its simplest form, it does not provide a direct way of classifying customers but provides a description of the cluster characteristics along with within-cluster models for the dependent variable of interest [2].

3.5 RFM Analysis

RFM analysis has been identified as a highly effective and widely used method for understanding customer behavior, enabling the development of predictive models related to customer engagement and loyalty [**10**]. RFM categorizes clients based on their past purchases by analyzing three key customer attributes: **Recency** (the date of the most recent purchase), **Frequency** (how often purchases are made), and **Monetary value** (the total value of purchases).

- **Recency** measures the time elapsed since a customer's last purchase. Customers who have made a purchase recently are considered more likely to engage again soon, reflecting their current interest in the brand.

- **Frequency** assesses how often a customer makes purchases over a specific period. Frequent buyers are typically more loyal and engaged with the brand, indicating a higher likelihood of repeat business.

- **Monetary value** evaluates the total amount a customer has spent. High spenders are often prioritized for premium marketing efforts as they contribute significantly to revenue.

By analyzing these three dimensions, RFM allows businesses to segment their customer base into groups with similar purchasing behaviors, which can then be targeted with tailored marketing strategies. This makes RFM an essential tool for defining and enhancing customer engagement, as it helps marketers identify the most valuable customers and understand how to maintain and increase their loyalty.

3.6 Market Gap

While CLV forecasts future customer value, RFM analysis offers immediate insights into consumer engagement by focusing on recent transactions. However, the effectiveness of these models in providing a comprehensive understanding of customer behavior is limited when used in isolation. The industry lacks a cohesive framework that integrates RFM and CLV to build a thorough customer profile, enabling companies to better understand and predict consumer behavior.

3.7 Proposed Marketing Opportunity

In this study, RFM and CLV will be combined to create a comprehensive customer profile. The key advantages include:

- **Hyper-Personalization:** By combining the short-term insights from RFM with the long-term predictions from CLV, personalized marketing campaigns can be developed to meet the needs of both current and potential customers.

- **Retention Optimization:** This approach identifies high-value, at-risk customers and explores ways to increase customer lifetime value, leading to more effective retention strategies.

- **Strategic Resource Allocation:** The integration of RFM and CLV provides marketers with a 360-degree view of their customer base, enabling more strategic resource allocation and more targeted marketing efforts.

Research Objectives

The aim of the study is to create a thorough framework for customer profiling. The main goal is to improve customer segmentation accuracy by developing an integrated customer profile model that incorporates Customer Lifetime Value (CLV) with RFM (Recency, Frequency, Monetary) analysis.

- **To Implement and Assess K-Means and XGBoost Algorithms:** The objective of this project is to deploy XGBoost for accurate customer profiling and to forecast consumer behaviors by using K-Means clustering for customer segmentation based on RFM and CLV metrics.

- **To Examine How Marketing Strategies Are Affected When RFM and CLV Are Combined:** The goal of the study is to better understand how combining RFM and CLV can enhance marketing campaigns and strategies by offering deeper insights into customer segments.

4 Methadology

A quantitative approach was employed for this study, as the primary objective was to analyze and interpret numerical data related to customer transactions. The choice to employ quantitative methods was made in order to leverage statistical and machine learning techniques to forecast future behaviors and to objectively evaluate and segment the client base. Robust analysis and the development of broadly applicable consumer profiles are made possible by this method.

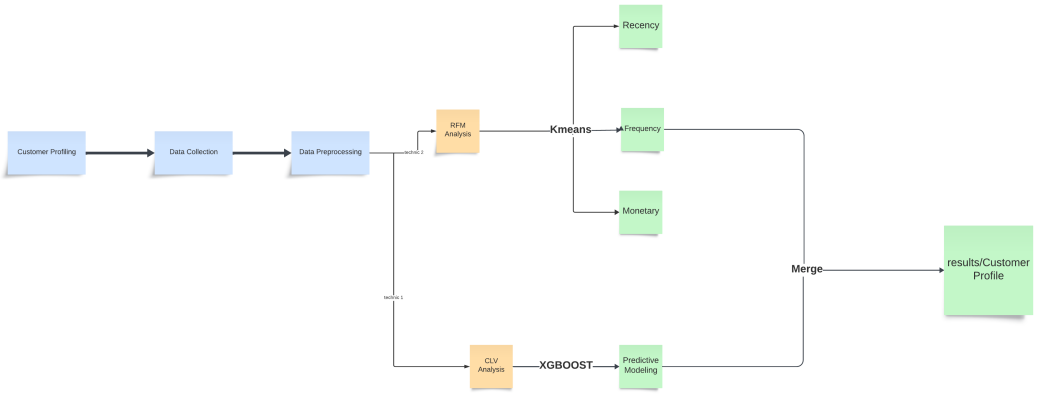

Figure 1: Concept Map of Customer Profiling

4.1 An explanation of techniques

Although RFM analysis and CLV are frequently used separately, this study integrates these measures in a novel way by utilizing XGBoost and K-Means clustering, two machine learning approaches. Although unusual, this combination is necessary to achieve a more thorough client profiling strategy. The RFM and CLV techniques are improved by the creative application of XGBoost to forecast future consumer value and behaviors, providing a more dynamic manner of client segmentation.

4.1.1 Data Collection

The transactional records of an online retailer over a predetermined time period provided the dataset for this study. Variables including transaction dates, purchase amounts, customer IDs, and demographic data were included in the data. This dataset was selected due to its wealth of detail and applicability to the goals of the study.

4.1.2 Data Analysis Methods

- **Data Preparation and Cleaning:**Preprocessing the data included normalizing it, addressing outliers, and checking for missing numbers. By taking this step, the data was verified to be appropriate for precise analysis.

- **RFM Analysis:** Recency, which indicates the amount of time since the last purchase, Frequency, which indicates the number of transactions, and Monetary, which indicates the total spending, were the three RFM metrics that were computed for each consumer. The first consumer segments were formed by scaling these data.

- **CLV Calculation:** To estimate each customer's future worth, CLV was computed using previous transaction data, accounting for average revenue and frequency of purchases.

- **K-Means clustering:** The elbow technique was used to calculate the number of clusters after K-Means clustering was applied to the RFM and CLV features. With the use of this technique, different client groups based on comparable purchase patterns might be identified.

- **Predictive Modeling with XGBoost:** XGBoost was utilized in predictive modeling to forecast customer outcomes including high-value customer identification and churn likelihood. RFM and CLV features were used to train the model, and hyperparameter optimization was done to maximize performance.

4.2 Goal

The goals of the research served as a guidance for the methodology selection. RFM analysis offered a basic client segmentation based on historical behavior, while CLV gave these profiles a forward-looking aspect. The customer profiles were validated through the use of XGBoost's predictive insights into consumer behavior and K-Means clustering, which made it easier to group customers into meaningful segments. These techniques were selected for the study because they compliment each other well and help achieve its objectives, despite the difficulty of combining them.

4.3 Obstacles and Solutions

The inconsistent quality of the data presented a problem, especially when handling outliers and missing numbers. Careful data pretreatment and cleaning was used to remedy this. Finding the ideal number of clusters for K-Means was another challenge, but it was overcome by employing the elbow approach and confirming the clusters with silhouette scores.

5 Implementation

5.1 Tools and Technologies

Technology/Library	Purpose	Reference
`Python`	Programming language for implementation	[6]
`Pandas`	Data manipulation and analysis	[12]
`NumPy`	Numerical operations	[13]
`scikit-learn (sklearn)`	Algorithms, preprocessing, clustering, metrics	[4]
`XGBoost`	Focused gradient boosting algorithm for classification	[3]
`statsmodels`	Statistical analysis	[5]
`Matplotlib`	Data visualization	[9]
`Seaborn`	Statistical data visualization	[18]

Table 1: Technologies and Libraries Used

5.2 Preprocessing of Data

- **Data Source** The UCI Machine Learning Repository's Online Retail dataset served as the study's data source.

- **Handling Missing Values** The **CustomerID** column was one of the first places where the dataset was checked for missing values. To verify the accuracy of the profiling procedure, any records lacking a **CustomerID** were eliminated, as customer profiling necessitates unique customer identifiers.

- **Filtering the Dataset** Since 88% of the dataset consisted of data from the United Kingdom, we concentrated exclusively on transactions from that country. This made it possible to create a consumer profile that was more pertinent and focused. - items having a negative number or other unnecessary or inconsistent data were eliminated since they could distort the analysis.

- **Scaling and Normalization** Scaling was used to the RFM values to guarantee that every dimension makes an equal contribution to the clustering process and to avoid the results being dominated by a single feature.

- **Final Dataset** Using clustering algorithms, only UK-based consumers with complete data were included in the final preprocessed dataset, which was then utilized to generate customer profiles.

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	InvoiceYearMonth	Monetary
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom	2010-12	15.30
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	2010-12	20.34
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom	2010-12	22.00
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	2010-12	20.34
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	2010-12	20.34

Figure 2: An overview of the dataset used in the study.

6 RFM Analysis

6.1 Objective

The purpose of the RFM (Recency, Frequency, Monetary) research was to create a dataset that could be used to target marketing campaigns by efficiently segmenting clients based on their purchase patterns.

6.2 Steps Involved

- **Recency Calculation**
  The number of days since each customer's last purchase was used to determine the Recency score. This measure aids in determining the frequency of a customer's interactions with the company.

- **Calculation of Frequency**
  The total number of transactions each client made during the observation period was counted to get the Frequency score. The degree of client loyalty and engagement is indicated by this score.

- **Monetary Calculation**
  By spotlighting high-value clients who make a substantial revenue contribution, the Monetary score was calculated based on the total amount spent by each customer. The calculation and subsequent segmentation were conducted using the K-Means algorithm, after determining the optimal number of clusters.

Scoring and Dataset Construction The metrics, namely Recency, Frequency, and Monetary, were evaluated separately using a standard 5-point rating system. Higher scores were indicative of more favorable consumer behavior. Each customer's total RFM score was then determined by adding up all of their individual scores. Each customer's ID, their unique R, F, and M scores, the total RFM score, and the associated segment were all included in the dataset that was created.

Logic of Customer Segmentation

The following categories were used to divide up the customer base according to their overall RFM score:

- **Customers with low value:** 0, 1, or 2.

- **Customers in the mid-value range:** 3 or 4.

- **Customers with high value:** 5 or 6.

- **Customers who are of the highest value:** 7 or 8.

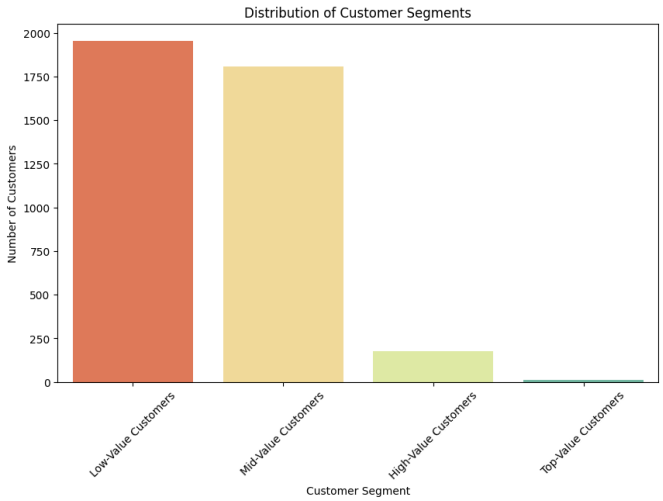

Figure 3: Customer Segmentation Based on RFM Scores

A function called `assign_segment(overallscore)` was used to implement this segmentation, allocating clients to segments according to their overall RFM Score.

Validation To verify the accuracy of the segmentation and guarantee the dependability of the outcomes, the dataset was examined using statistical methods from the statsmodels package.

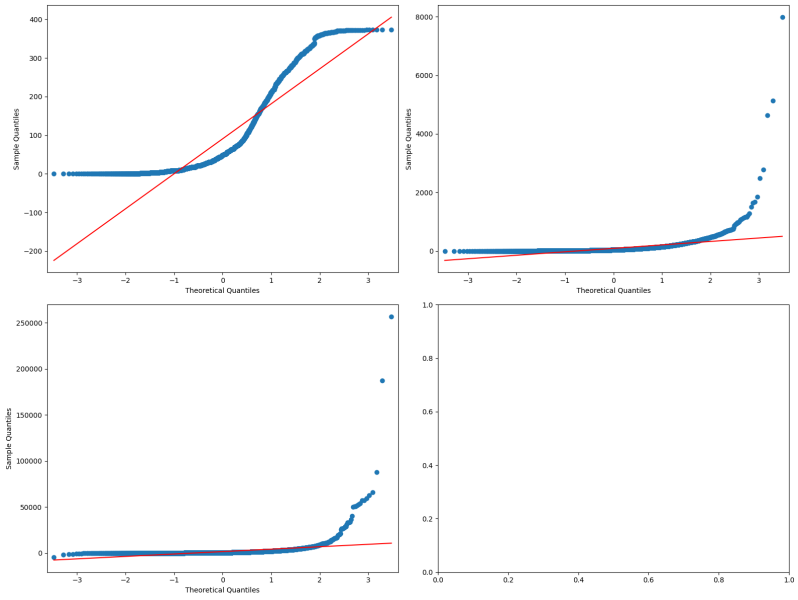

Figure 4: Customer Segmentation Based on RFM Scores Using Kmeans

Limitations and Integration Although the RFM analysis yielded insightful information, it presented the data from a single point of view. Further analyses were conducted to obtain a more comprehensive perspective, including the integration of Customer Lifetime Value (CLV).

6.3 Results and Visualization

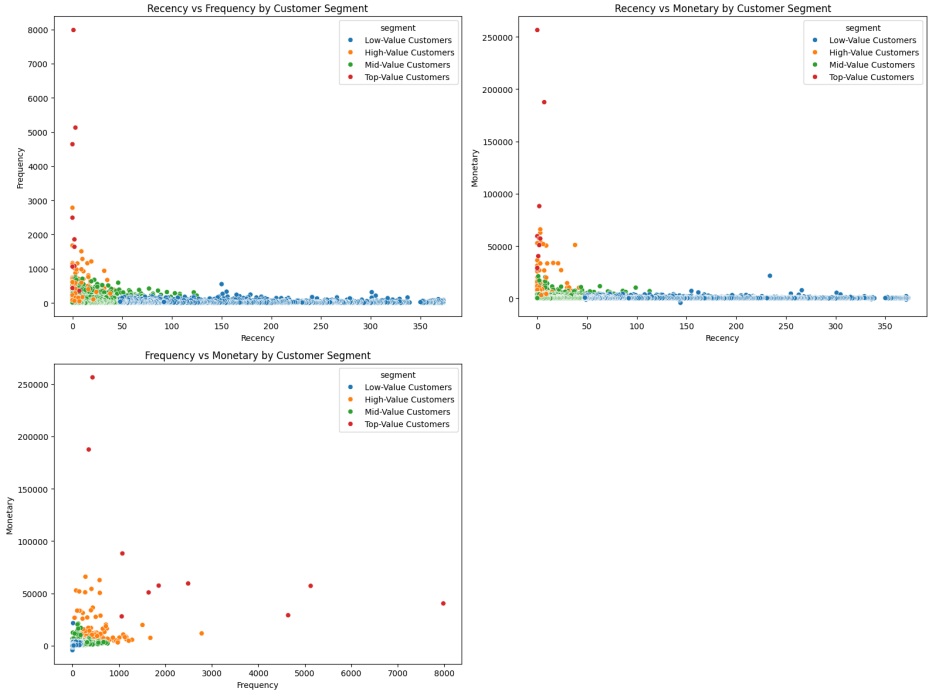

Figure 5: Customer Segmentation Based on RFM Scores Using Kmeans

7 Customer Lifetime Value (CLV)

To calculate and analyze Customer Lifetime Value (CLV), we performed a process similar to the RFM (Recency, Frequency, Monetary) segmentation but focused on predicting CLV for each customer. The process is outlined below:

7.1 Data Preparation

- **Sorting Data:** The dataset was filtered to include only transactions from UK customers.
- **Time Period Division:** The data was divided into two periods:
  - **m3:** For model training.
  - **m6:** For model validation.

7.2 Feature Engineering

- **K-Means Clustering:** Clusters for **Recency**, **Frequency**, and **Monetary** were created using K-Means clustering.
- **Overall Score Calculation:** An **Overall Score** was calculated to segment the customer base into four categories: **Low**, **Mid**, **High**, and **Top**.
- **Target Variable Preparation:** The **monetary value (m6_Monetary)** for the next six months was calculated to prepare the target variable for the model.

7.3 Cluster Establishment and Arrangement

- **LTV Clustering:** Customers were grouped into distinct **LTV clusters** based on their **m6_Monetary** values using K-Means clustering.

- **Cluster Ordering:** The clusters were arranged to correspond with the increasing or decreasing value of **m6_Monetary**.

7.4 Modeling

To get the data ready for machine learning models, create dummy variables. Test different machine learning techniques for LTV cluster prediction, such as XGBoost, Decision Trees, KNN, and Logistic Regression. Utilize measures like precision and accuracy to assess the model's performance. which indicate that logistic regression gave the best results yet when we invistigate even further we realize that xgboost made the best recall, precision and accuracy verall classes

```
LR: 0.802789 (0.032673)
XGB: 0.768655 (0.025433)
KNN: 0.790654 (0.031085)
DT: 0.792391 (0.025086)
RF: 0.784860 (0.029133)
ADA: 0.770403 (0.031987)
SVC: 0.777336 (0.045422)
```

Figure 6: Modeling results showing the segmentation based on RFM analysis and CLV predictions.

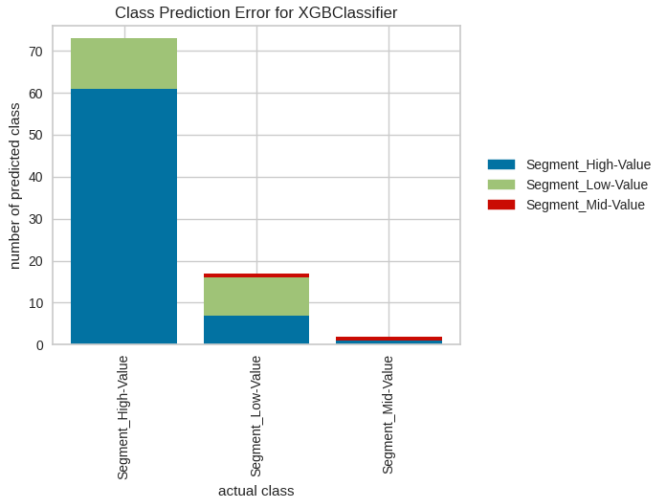

Figure 7: XGBoost Results

7.5 Validation

7.5.1 ROC AUC

he ROC curve results indicate that the XGBClassifier performs well overall, with a macro-average AUC of 0.90 and a micro-average AUC of 0.94. Among the classes, the `Segment_Mid-Value` class achieves the highest AUC

of 0.98, while the `Segment_Low-Value` class has the lowest AUC of 0.84. This suggests that distinguishing the `Segment_Low-Value` class poses some difficulty.

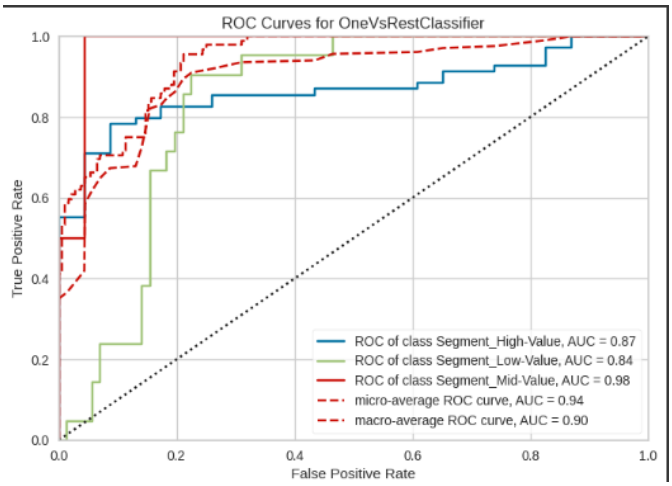

Figure 8: ROC AUC Curve

7.5.2 Precision Recall

The Precision-Recall curve shows an average precision of 0.89, reflecting a strong balance between precision and recall. The model is effective at identifying relevant instances with few false positives.

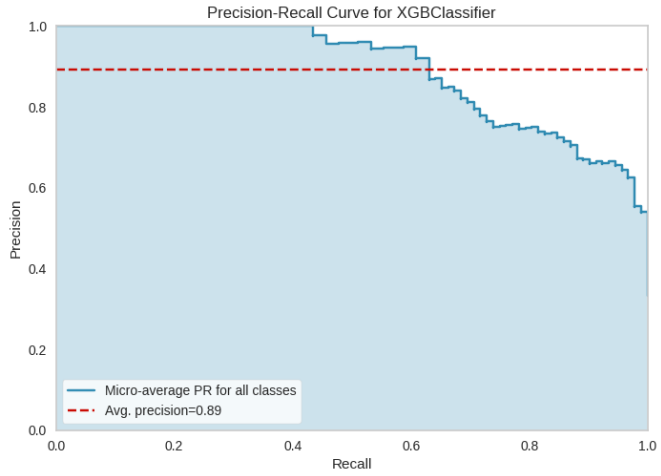

Figure 9: Precision-Recall Curve

8 Integration

Figure 10 illustrates the distribution of RFM clusters, with Customer Lifetime Value (CLV) represented as the hue. This visualization provides insight into how CLV varies across different RFM clusters.

8.1 Cross-Cluster Distribution

The plot highlights a crossover effect where the distribution of CLV clusters varies across RFM clusters. Specifically, customers in certain RFM clusters exhibit varying CLV levels. This indicates that CLV does not uniformly correlate with RFM, revealing that customers within a single RFM cluster can have diverse CLV profiles.

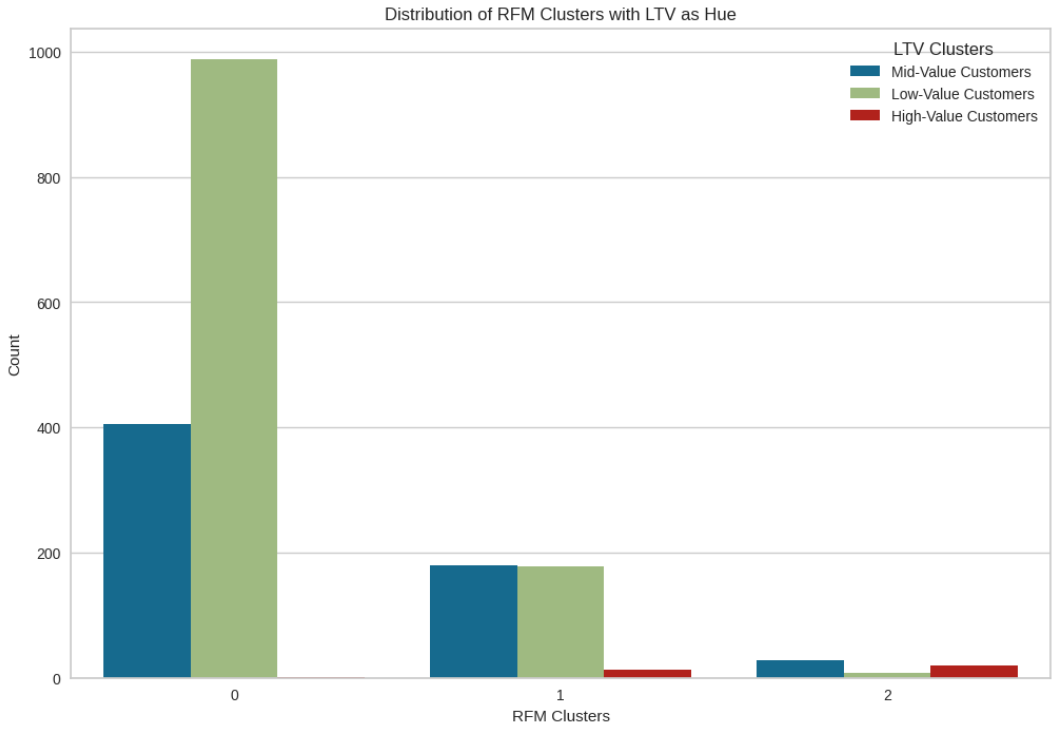

Figure 10: Distribution of RFM Clusters with CLV as Hue

8.2 Complementary Perspectives

The presence of different CLV levels within RFM clusters demonstrates the complementary nature of these analyses. While RFM provides a snapshot of recent customer activity, CLV offers a perspective on the total value over time. The variation in CLV across RFM clusters emphasizes the need to consider both metrics for a comprehensive customer assessment.

8.3 Strategic Implications

The variation in CLV within RFM clusters suggests that recent activity alone may not fully capture customer value. Marketing strategies should aim to re-engage customers in low RFM clusters who may still have high CLV potential. Additionally, strategies for high RFM but low CLV segments should focus on enhancing long-term value, possibly through loyalty programs or targeted offers.

9 Conclusion

Customer Lifetime Value (CLV) modeling and Recency, Frequency, Monetary (RFM) analysis together provide a thorough method of customer profile that bridges the gap between current and future customer value evaluations. This study effectively illustrates how the combination of these methodologies improves the accuracy of consumer segmentation, allowing companies to create more focused marketing campaigns, allocate resources more efficiently, and make better decisions based on insights from data. The integrated approach makes it easier to create precise and useful customer profiles by offering a more detailed understanding of customer behavior. This, in turn, improves customer engagement and boosts revenue. The model performed well in identifying Mid-Value clients, demonstrating that the research objectives of increasing client segmentation accuracy and personalizing marketing activities were effectively handled. Nonetheless, the noted difficulties in categorizing Low-Value examples point to areas that require more improvement. Subsequent investigations may investigate the integration of supplementary factors or sophisticated machine learning methodologies to augment the model's efficacy throughout all consumer segments, specifically for those more elusive categories.

here is my github repository for the whole project and extra analysis [1]

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