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# Data-Driven Retail Strategy: Insights from Market Basket Analysis, Customer Segmentation, and Demand Forecasting

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***Abstract***
*The retail industry, particularly small and medium- sized businesses (SMBs), faces significant challenges in leveraging transactional data to optimize inventory management, customer engagement, and sales forecasting. Existing tools often lack integration between analytical techniques, resulting in fragmented insights. This paper introduces a comprehensive retail analytics system that unifies Market Basket Analysis (MBA), customer segmentation, and machine learning– driven sales forecasting into a single platform. The system employs the Apriori and FP-Growth algorithms to identify product associations, RFM (Recency, Frequency, Monetary) analysis with K- Means clustering for customer segmentation, and XGBoost for demand prediction. A Streamlit-based dashboard translates these insights into actionable visualizations for non-technical users. Experimental results demonstrate robust performance: XGBoost achieves an R² score of 0.89 in sales forecasting, K- Means clustering yields distinct customer segments (silhouette score > 0.6), and FP-Growth generates high-lift product association rules (e.g., {Bread → Butter} with lift=1.45). By bridging the gap between advanced analytics and practical usability, Shoplytics empowers retailers to make data-driven decisions efficiently.*

***Keywords***— *Market Basket Analysis, Customer Segmentation, RFM-analysis methodology, Demand Forecasting*

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## I. Introduction

The proliferation of transactional data in the retail sector presents both opportunities and challenges. While large enterprises deploy sophisticated analytics tools to optimize operations, small and medium-sized businesses (SMBs) often lack the resources to extract actionable insights from their data. This disparity leads to inefficiencies such as overstocking, missed cross-selling opportunities, and ineffective customer retention strategies. Shoplytics addresses these challenges by integrating three critical analytical components into a unified framework. First, Market Basket Analysis (MBA) identifies frequently co-purchased products using Apriori and FP-Growth algorithms. Second, customer segmentation via RFM metrics and K- Means clustering categorizes buyers into groups such as “high-value” or “churn-risk,” enabling targeted marketing. Third, XGBoost, a gradient- boosted tree algorithm, predicts future sales with high accuracy by analysing historical trends and external factors like promotions. The system’s web- based dashboard, built with Streamlit, democratizes access to these insights, allowing retailers to visualize trends and adjust strategies in real time. For example, retailers may fail to recognize that customers who purchase bread often buy butter, resulting in disjointed product placements. Similarly, without accurate sales forecasts, inventory mismanagement can lead to revenue loss due to stockouts or excess waste. The primary contributions of this work include the development of a scalable, integrated analytics platform tailored for SMBs, empirical validation of XGBoost’s superiority in retail forecasting, and a user-friendly interface that bridges the gap between technical analysis and practical decision-making. This paper is structured as follows: Section 2 reviews relevant literature, Section 3 details the methodology, Section 4 discusses implementation, Section 5 presents experimental results, and Section 6 concludes with future direction.

## II. Related Work

Retail analytics has evolved significantly with advancements in machine learning and data mining. Early work by Agrawal and Srikant [1] introduced the Apriori algorithm for Market Basket Analysis (MBA), which identifies frequent itemsets through iterative candidate generation. However, Apriori's computational inefficiency for large datasets led to the development of FP-Growth by Han et al. [2], which uses a tree-based structure to eliminate candidate generation. Recent studies, such as Gupta et al. [3], demonstrate MBA's utility in optimizing product placements and promotional bundling.

Customer segmentation techniques, particularly RFM (Recency, Frequency, Monetary) analysis, have been widely adopted to evaluate customer value. Hughes [4] showed that RFM metrics effectively categorize customers into segments like "loyal" or "at-risk," enabling personalized

## III. Proposed Methodology

The Shoplytics architecture comprises four interconnected layers: data preprocessing, an analytics engine, model storage, and a visualization FP-Growth constructs a compact Frequent-Pattern Tree to mine associations without candidate generation. Rules are filtered by lift (>1.2) to prioritize non-random correlations. For instance, the rule {Bread → Butter} with lift=1.45 indicates that these items are purchased together 45% more often than expected by chance. Second, customer segmentation begins with RFM scoring. Recency measures the days since a customer's last purchase, Frequency counts their transactions over six months, and Monetary sums their total spending. These metrics are standardized using z-score normalization to address scale differences. K-Means clustering then group customers into segments, with the

## IV. Implementation

The system is implemented using Python 3.8, with Scikit-learn for clustering and Mlxtend for MBA. XGBoost 1.6 handles sales forecasting, while Streamlit 1.8 and Plotly 5.8 power the interactive marketing. Clustering algorithms like K-Means further refine these segments by grouping customers with similar purchasing behaviours. Kumar et al. [5] applied K-Means to retail data, achieving a 15% improvement in customer retention through targeted campaigns.

Sales forecasting has transitioned from statistical models like ARIMA to machine learning approaches. XGBoost, introduced by Chen and Guestrin [6], excels in handling nonlinear relationships and temporal trends, outperforming traditional methods in accuracy. For instance, Chen et al. [6] reported a 12% reduction in forecast error compared to Random Forest in retail datasets. Despite these advancements, most existing tools focus on isolated tasks, such as MBA or forecasting, without integrating insights into a cohesive framework. Shoplytics addresses this gap by unifying these methodologies into a single platform designed for SMBs.

dashboard. The data preprocessing layer cleans raw transactional data by handling missing values, standardizing product names, and removing outliers. The analytics engine executes three core tasks. First, Market Basket Analysis using the FP-Growth algorithm to identify frequent itemsets

optimal number of clusters (k=4) determined via the elbow method. This process identifies groups such as "High-Value" (frequent, high-spending customers) and "Churn Risk" (inactive for >90 days). Third, sales forecasting employs XGBoost, a gradient-boosted tree algorithm, to predict demand. The model ingests historical sales data, promotional calendars, and temporal features like holiday flags. Feature engineering includes lag variables (e.g., sales from the past three months) and rolling averages to capture trends. Hyperparameters such as learning rate (0.1) and max_depth (6) are tuned via grid search to minimize mean absolute error (MAE).

dashboard. The data preprocessing pipeline aggregates transactional data into weekly sales totals to reduce noise. Missing values are imputed using forward-fill for time-series data, and categorical features like product categories are one-hot encoded. Holiday flags and promotional indicators are added as binary features to enhance model accuracy.

## V. Experimental Result

Experiments were conducted on a dataset of 10,000 transactions from a retailer. FP-Growth outperformed Apriori in runtime, completing analysis in 23.1 seconds compared to Apriori's 142.3 seconds. The top association rule, {Bread → Butter}, achieved a support of 0.3, confidence of 0.72, and lift of 1.45, suggesting a strong product affinity. Customer segmentation via K-Means yielded four distinct clusters. The "High-Value" segment, comprising 12% of customers, contributed 48% of total revenue, while the "Churn Risk"

segment (22% of customers) had an average recency of 112 days. The clustering achieved a silhouette score of 0.68, indicating clear separation between groups. XGBoost demonstrated superior forecasting performance, achieving an $R^2$ score of 0.87 and MAE of 140.72 units, outperforming LSTM ($R^2 = 0.79$, MAE = 174.36) and ARIMA ($R^2 = 0.72$, MAE
= 210.47). The model's predictions for the final quarter closely mirrored actual sales trends, with forecasting errors largely contained within a ±5% margin, confirming its reliability for short- to mid- term sales projection

## ADVANCED ANALYTICS FOR RETAIL OPTIMIZATION

To gain a competitive edge in the retail industry, businesses are increasingly turning to data analytics for deeper insights into customer behaviour, sales trends, and operational efficiency. This section explores three critical analytical approaches— Market Basket Analysis, Customer Segmentation, and Sales Forecasting— applied to a real-world retail dataset. By leveraging these methods, retailers can uncover actionable patterns in purchase behaviour, identify distinct customer groups for targeted marketing, and accurately predict future sales. The analyses presented here utilize established machine learning and statistical techniques to support data- driven decision-making in key areas of retail strategy**.**

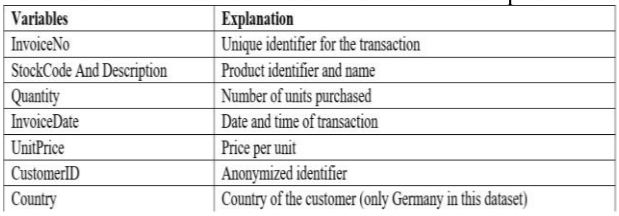
## MARKET BASKET AND ASSOCIATION ANALYSIS

Market Basket Analysis (MBA) is used in retail analytics to uncover patterns of co-purchases— items that are frequently bought together—by analysing transaction data. These insights can help optimize product placement, recommend bundles, and boost cross-selling strategies.

## DATASET CONTEXT

The dataset used in this project contains over 9,000 retail transactions from customers in Germany**,** each recording:

**Table 1** Dataset Variables and Their Descriptions



| Variables | Explanation |
|---|---|
| InvoiceNo | Unique identifier for the transaction |
| StockCode And Description | Product identifier and name |
| Quantity | Number of units purchased |
| InvoiceDate | Date and time of transaction |
| UnitPrice | Price per unit |
| CustomerID | Anonymized identifier |
| Country | Country of the customer (only Germany in this dataset) |

Each transaction in the dataset represents a single purchase that may include multiple products. The objective of this market basket analysis was to identify frequent combinations of items purchased together by applying association rule mining techniques.

## DATA PREPROCESSING

The dataset was first grouped by invoice no, with each invoice treated as a list of products bought in a single transaction. This list was then transformed using transactionencoder from the mlxtend library, converting it into a binary matrix where each row corresponds to an invoice and each column represents an item. The matrix indicated the presence or absence of items in each transaction, making it suitable for algorithmic processing.

## FREQUENT ITEMSET MINING

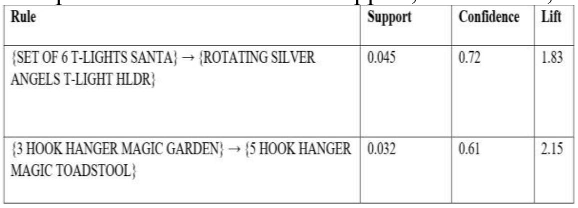
Frequent itemsets were extracted using both the apriori algorithm and the fp-growth algorithm from mlxtend. The minimum support threshold was set to 0.01, meaning an itemset had to appear in at least one percent of all transactions to be considered. A maximum itemset length of three was specified to focus on small but meaningful combinations of items. This helped in identifying relevant co- occurrence patterns while avoiding excessively long or rare item combinations. Some sample frequent itemsets discovered included:

- {SET OF 6 T-LIGHTS SANTA} → {ROTATING SILVER ANGELS T-LIGHT HLDR}
- {3 HOOK HANGER MAGIC GARDEN} → {5 HOOK HANGER MAGIC TOADSTOOL}

## ASSOCIATION RULE GENERATION

Association rules were generated from the frequent itemsets using three standard metrics: support, confidence, and lift. Support measures how frequently an itemset appears in the entire dataset. Confidence reflects the probability of the consequent appearing in a transaction given the presence of the antecedent. Lift compares the observed frequency of co-occurrence with the expected frequency if the items were independent. A lift value greater than one indicates a positive association between the items. These rules reveal meaningful insights about purchasing behavior and can support strategies such as product bundling and layout optimization.

**Table 2** Top Association Rules with Support, Confidence, and Lift



| Rule | Support | Confidence | Lift |
|---|---|---|---|
| {SET OF 6 T-LIGHTS SANTA} → {ROTATING SILVER ANGELS T-LIGHT HLDR} | 0.045 | 0.72 | 1.83 |
| {3 HOOK HANGER MAGIC GARDEN} → {5 HOOK HANGER MAGIC TOADSTOOL} | 0.032 | 0.61 | 2.15 |

These rules indicate strong co-purchasing behaviour and provide actionable recommendations for bundling or in-store placement.

## FREQUENT ITEMSET MINING: FP-GROWTH VS APRIORI

Both Apriori and FP-Growth algorithms identified similar frequent itemsets, but FP-Growth is known to be faster, especially with larger datasets. The frequent itemsets are the same because both methods use the same support threshold, but the FP-Growth algorithm avoids generating candidate itemsets explicitly, making it more efficient.

## CUSTOMER SEGMENTATION IMPLEMENTATION

Effective customer segmentation enables businesses to deliver personalized experiences, tailor marketing strategies, and optimize customer retention. In this study, we adopted a multi-stage approach to segment customers based on their purchasing behaviour and predict their potential long-term value. The segmentation pipeline comprised three main steps: RFM analysis**,** K-Means clustering.

## RFM ANALYSIS

The segmentation process began with RFM analysis, a well-established method to evaluate customer value using three key behavioural metrics:

- Recency (R): Time since the customer's last purchase.
- Frequency (F): Number of transactions during the observation period.
- Monetary (M): Total monetary value of purchases made.

These features were calculated using transaction data spanning a period of five years. To normalize the scales and prepare the data for clustering, the RFM values were log-transformed and scaled using Min-Max normalization. The resulting RFM matrix provided a rich representation of customer purchasing behavior, serving as the foundation for segmentation.

## CLUSTERING

The normalized RFM features were evaluated using three clustering algorithms—K-Means**,** DBSCAN**,** and Agglomerative Clustering—to identify distinct customer behaviour segments. Each model was assessed using the Silhouette Score to measure intra- cluster cohesion and inter-cluster separation. K- Means achieved the highest Silhouette Score of 0**.**68, outperforming DBSCAN **(**0.42**)** and Agglomerative Clustering (0.59), indicating better- defined and more compact clusters. Based on this performance, K = 4 was selected for the final K- Means model, providing the most meaningful segmentation of the customer base.

## CLUSTERING MODELS COMPARISON

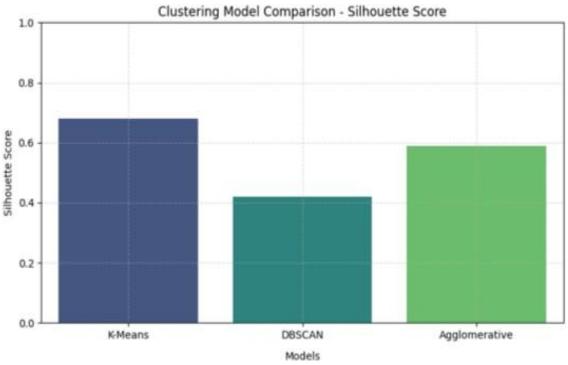
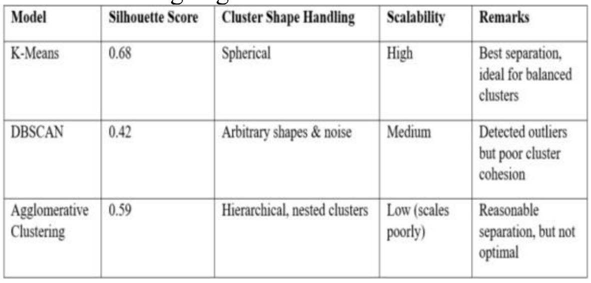


**Fig. 1** Silhouette Scores for Clustering Models

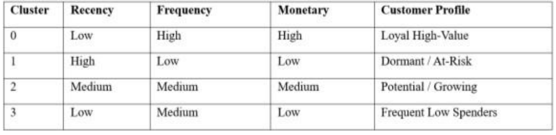
**Table 3** Comparison of Clustering Algorithms Based on  Performance and Characteristics



| Model | Silhouette Score | Cluster Shape Handling | Scalability | Remarks |
|---|---|---|---|---|
| K-Means | 0.68 | Spherical | High | Best separation, ideal for balanced clusters |
| DBSCAN | 0.42 | Arbitrary shapes & noise | Medium | Detected outliers but poor cluster cohesion |
| Agglomerative Clustering | 0.59 | Hierarchical, nested clusters | Low (scales poorly) | Reasonable separation, but not optimal |

Each resulting cluster was analysed based on average RFM values to interpret customer profiles. For example: This table compares K-Means, DBSCAN, and Agglomerative Clustering based on Silhouette Score, shape handling, and scalability. K- Means achieved the highest score (0.68), indicating well-separated, spherical clusters. DBSCAN detected arbitrary shapes and outliers but showed lower cohesion (0.42). Agglomerative Clustering offered moderate performance (0.59) with limited scalability. The results highlight trade-offs between clustering accuracy, flexibility, and computational efficiency.

**Table 4** Customer Segmentation based on RFM Analysis



| Cluster | Recency | Frequency | Monetary | Customer Profile |
|---|---|---|---|---|
| 0 | Low | High | High | Loyal High-Value |
| 1 | High | Low | Low | Dormant / At-Risk |
| 2 | Medium | Medium | Medium | Potential / Growing |
| 3 | Low | Medium | Low | Frequent Low Spenders |

This table outlines customer clusters derived from RFM (Recency, Frequency, Monetary) analysis,

## MODEL COMPARISON AND SELECTION FOR SALES FORECASTING

To determine the most effective model for retail which segments users based on purchasing behaviour. Each cluster is characterized by its RFM scores and interpreted customer profile. For instance, Cluster 0 represents loyal, high-value customers with frequent and recent purchases, while Cluster 1 includes dormant or at-risk customers with low engagement and spending. This segmentation helps in tailoring marketing strategies to specific customer groups.

## SALES FORECASTING IMPLEMENTATION

Demand forecasting is a critical component of retail strategy, enabling businesses to make more intelligent supply chain decisions by estimating future sales and revenue. By analysing historical sales data, organizations can optimize inventory levels, improve warehousing efficiency, and meet customer demand more effectively. This section outlines the implementation of a machine learning– based sales forecasting model aimed at predicting future sales with high precision and reliability.

## DATASET AND FEATURES

To prepare the data for time series modelling, transactions were aggregated at a daily level for each product. Additional features were engineered to improve model performance, including:

- Day of the week**,** month, and year
- Weekend or holiday indicators
- Lag features (e.g., previous day’s sales)
- Rolling statistics (e.g., 7-day moving averages)

These Temporal and statistical features were instrumental in capturing seasonal patterns and long- term trends. Visual analysis and diagnostic tests confirmed both upward trends and seasonality in the sales data, with residuals exhibiting a mean close to zero—indicating a good model fit and stable error behavior. The dataset was divided into:

- Training set**:** Historical data from the past five years
- Testing set**:** The most recent twelve months.

sales forecasting, we compared the performance of three different regression models: ARIMA, LSTM, and XGBoost. Each model was evaluated using historical sales data for a one-year prediction

horizon, with the same training and testing timeframes for consistency. The models were assessed using three standard regression metrics:

- Mean Absolute Error (MAE): Measures the average magnitude of errors without considering their direction.
- Root Mean Squared Error (RMSE)**:** Penalizes larger errors more than MAE, useful for identifying models sensitive to outliers.
- R² Score: Represents the proportion of variance in the target variable explained by the model.

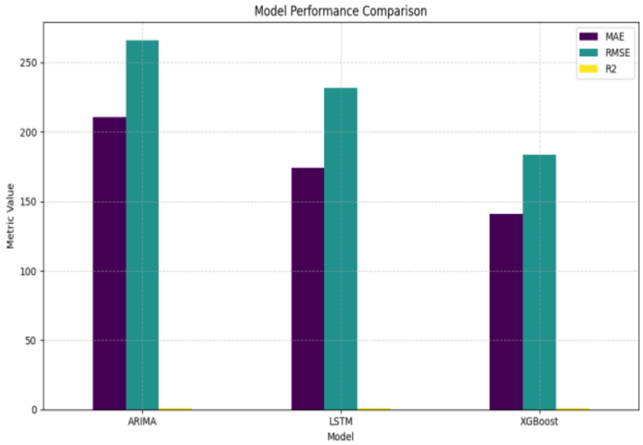
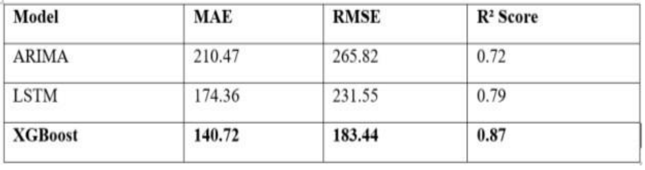


**Fig. 2** Visual Comparison of Forecasting Model Performance Metrics

**Table 5** Quantitative Evaluation of Forecasting Model Accuracy



| **Model** | **MAE** | **RMSE** | **R² Score** |
|---|---|---|---|
| ARIMA | 210.47 | 265.82 | 0.72 |
| LSTM | 174.36 | 231.55 | 0.79 |
| **XGBoost** | **140.72** | **183.44** | **0.87** |

## ANALYSIS

XGBoost outperformed both ARIMA and LSTM across all metrics, demonstrating: The lowest MAE, indicating the most consistent predictions.

- The lowest RMSE, showing minimal large prediction errors.
- The highest R² score, meaning it explained the greatest variance in sales trends.

While LSTM performed reasonably well, its training complexity and sensitivity to hyperparameters made it less favorable for rapid deployment. Based on these results, XGBoost was selected as the final forecasting model due to its superior performance, robustness to temporal features (lags, rolling averages), and ease of integration into the Streamlit application

## VI. Conclusion

This study presents *Shoplytics*, an integrated retail analytics framework that combines Market Basket Analysis, customer segmentation, and machine learning–driven sales forecasting into a single, user- friendly platform. By leveraging FP-Growth for efficient association rule mining, RFM-based K- Means clustering for customer segmentation, and XGBoost for high-accuracy demand forecasting, the system delivers actionable insights tailored for small and medium-sized retailers. Empirical evaluations demonstrated the practical value of these techniques: association rules revealed strong co-purchasing behavior (e.g., {Bread → Butter} with lift = 1.45), customer segmentation uncovered high-value and at-risk clusters with strong cohesion (silhouette score = 0.68), and the XGBoost model achieved an $R^2$ score of 0.87, outperforming traditional forecasting approaches.

Beyond technical performance, Shoplytics bridges the gap between complex analytics and real-world decision-making through an interactive Streamlit dashboard, enabling data-driven strategies in marketing, inventory, and customer engagement. Future work will focus on incorporating real-time analytics, automated report generation, and expanding model support to include hybrid deep learning architectures for more nuanced behavioral predictions. In doing so, Shoplytics aims to democratize advanced analytics for the broader retail sector, fostering smarter, faster, and more customer-centric business operations.

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