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**PROJECT NAME : Customer Segmentation & Market
Basket Intelligence Platform**

GITHUB LINK : <https://github.com/GaneshLathin/Customer-Segmentation-Market-Basket-Intelligence-Platform>

Customer Segmentation & Market Basket Intelligence Platform

Problem Statement

An e-commerce business generates hundreds of thousands of transaction records annually across thousands of customers and products. However, without structured analysis, it becomes extremely difficult to identify high-value customers, detect at-risk customers, understand purchasing patterns, or create targeted marketing strategies.

Traditional rule-based segmentation techniques fail to capture complex behavioral patterns hidden in large transactional datasets. Manual analysis is inefficient and prone to oversight, especially when dealing with multi-dimensional customer features such as recency, frequency, and monetary value.

Therefore, there is a need for an intelligent analytics platform that applies unsupervised machine learning algorithms to automatically discover meaningful customer segments, reduce data complexity, uncover product associations, and generate actionable marketing personas. This project addresses that need through the development of SegmentIQ.

Objectives

The main objectives of this project are:

1. To ingest and clean raw transactional data into a structured customer-level dataset.
2. To engineer RFM (Recency, Frequency, Monetary) features along with additional behavioral metrics.
3. To apply multiple unsupervised clustering algorithms for automated customer segmentation.

4. To reduce high-dimensional customer data using dimensionality reduction techniques.
5. To perform market basket analysis to identify product association patterns.
6. To generate interpretable marketing personas based on cluster characteristics.
7. To build an interactive full-stack web dashboard for real-time analytics visualization.

Model Implementation :

Unsupervised Machine Learning for Customer Segmentation:

SegmentIQ applies multiple clustering and analytical techniques:

1. K-Means Clustering:

Uses centroid-based partitioning to divide customers into optimal segments based on behavioral similarity.

2. Agglomerative Hierarchical Clustering:

Builds a bottom-up dendrogram structure to represent hierarchical merging of customers.

3. DBSCAN (Density-Based Spatial Clustering):

Identifies arbitrarily shaped clusters and detects anomalous customers as noise points.

Steps involved:

- Perform exploratory data analysis (EDA)
- Aggregate invoice-level data into customer-level features
- Engineer RFM and derived behavioral metrics
- Apply log transformation (\log_{10}) to reduce skewness
- Standardize features using z-score normalization
- Determine optimal cluster parameters using silhouette score
- Train clustering models
- Interpret cluster characteristics

Feature Engineering:

Customer-level features include:

- Recency (Days since last purchase)
- Frequency (Number of unique invoices)
- Monetary Value (Total spending)
- Average Order Value
- Total Items Purchased
- Unique Products Bought
- Average Basket Size

Dimensionality Reduction:

To visualize high-dimensional customer data:

1. PCA (Principal Component Analysis):

Reduces multi-dimensional feature space into principal components while retaining maximum variance.

2. LDA (Linear Discriminant Analysis):

Uses cluster labels as targets to maximize separation between discovered segments.

Techniques used:

- Explained variance ratio analysis
- Component loading interpretation
- 2D and 3D visualization of clusters

Market Basket Analysis:

The Apriori algorithm is applied to extract frequent itemsets and association rules from transaction data.

- Identify frequently co-purchased products
- Generate rules using support, confidence, and lift
- Rank product relationships by lift ratio
- Visualize product co-occurrence using heatmaps

Hyperparameter Tuning:

The following parameters are optimized:

- k (Number of clusters in K-Means)
- eps (Neighborhood radius in DBSCAN)
- min_samples (Minimum points for density cluster)
- min_support (Apriori support threshold)

Techniques used:

- Elbow method for inertia analysis
- Silhouette score comparison
- Dendrogram analysis
- Lift-based ranking of association rules

Performance Evaluation:

Clustering models are evaluated using unsupervised performance metrics.

The following metrics are used:

- Silhouette Score
- Inertia (Within-cluster sum of squares)
- Davies-Bouldin Index
- Explained Variance Ratio (PCA)
- Support, Confidence, and Lift (Apriori)

System Architecture:

Backend:

- Python 3.11
- FastAPI framework
- scikit-learn, SciPy, mlxtend
- Automatic dataset download from UCI repository
- REST API endpoints for clustering and analytics

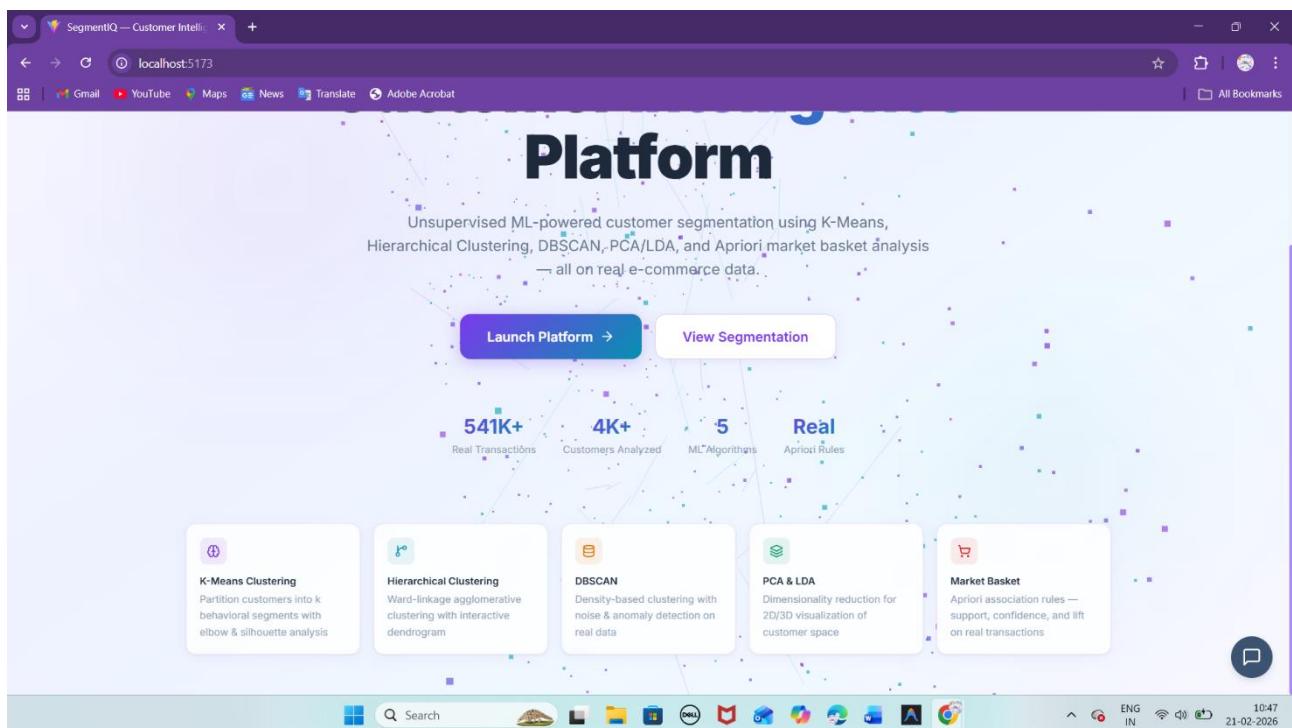
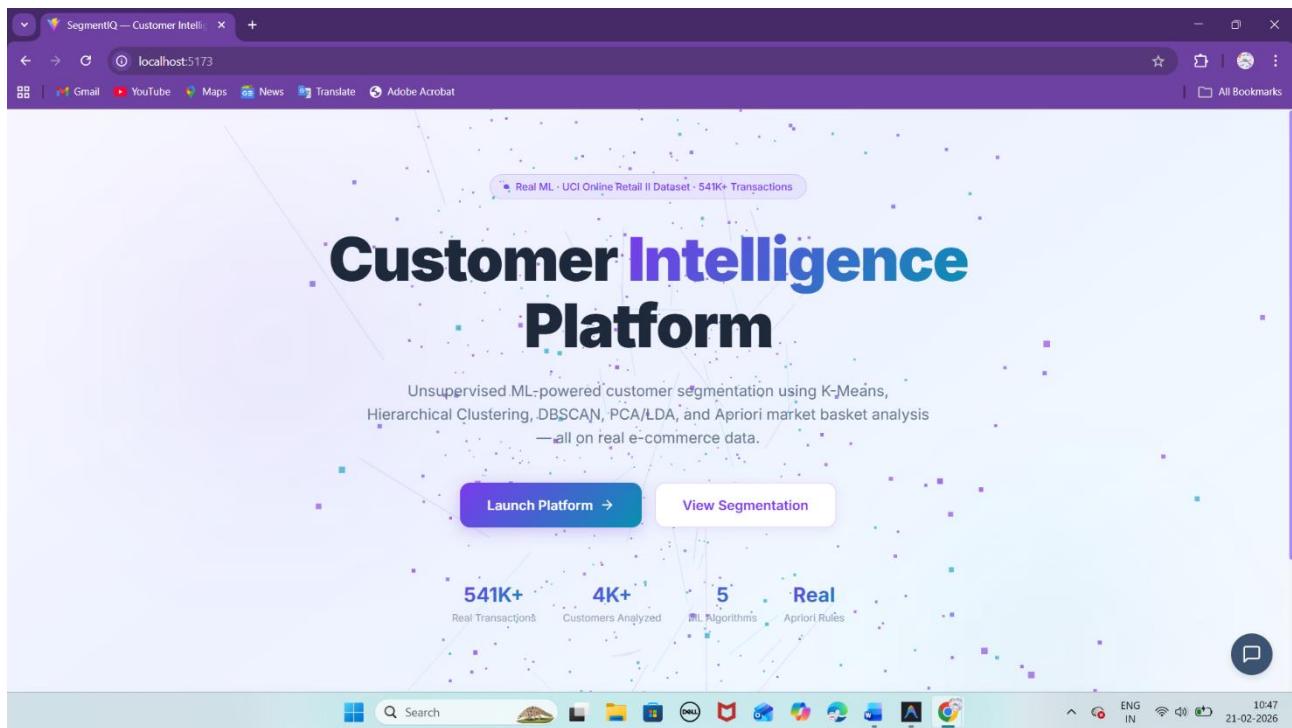
Frontend:

- React 18 with Vite
- Tailwind CSS styling
- Recharts for data visualization
- Three.js for 3D background
- Framer Motion & GSAP for animations
- Axios for API communication

Results and Outcomes:

- Successful segmentation of customers into meaningful behavioral groups
- Silhouette score of approximately 0.42 using K-Means
- Identification of high-value “Champion” customers
- Detection of 5–12% anomalous customers using DBSCAN
- PCA explaining approximately 65–70% variance in first two components
- Discovery of high-lift product association rules
- Generation of actionable marketing personas with campaign recommendations
- Interactive real-time dashboard for business decision support

Output:



SegmentIQ — Customer Intelligence Platform

localhost:5173/dashboard

Backend: localhost:8000

Dashboard UCI Online Retail II · Real ML Analysis

Dataset Period: 2009-12-01 – 2011-12-09 UCI Online Retail II (id=502)

Segmentation Dim. Reduction Market Basket Reports

Real data Analyzed SKUs GBP Per invoice Markets

805,549 Total Transactions **5,878** Unique Customers **4,631** Unique Products **£17743K** Total Revenue **£22.03** Avg Order Value **41** Countries

Customer Segment Distribution Expected cluster distribution across personas

Champions (22%) Loyal (31%) At-Risk (18%) New (19%) Lost (10%)

Algorithm Comparison Silhouette scores across clustering methods

Clustering Method	Silhouette Score
K-Means	~0.42
Hierarchical	~0.38
DBSCAN	~0.28

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SegmentIQ — Customer Intelligence Platform

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Feature Engineering RFM Analysis Recency, Frequency, Monetary features engineered from real invoice data. Log-transformed to handle skewness.

DBSCAN Noise Detection DBSCAN identifies anomalous customers who don't fit any cluster profile. Useful for fraud or data quality issues.

Market Basket Association Rules Apriori algorithm mines frequent itemsets from real basket data. Top rules sorted by lift ratio.

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SegmentIQ — Customer Intelligence Platform

localhost:5173/segmentation

Customer Segmentation
UCI Online Retail II - Real ML Analysis

Backend: localhost:8000

Customer Segmentation
Real RFM features from UCI Online Retail II - 4K+ customer profiles

K-Means **Hierarchical** **DBSCAN**

Number of Clusters (k) **4** Silhouette: 0.31 Customers clustered: 1,000
2 10

Customer Cluster Scatter (PCA 2D)
Customers projected to 2D via PCA, colored by cluster

Elbow Curve
Inertia vs. number of clusters — choose the elbow point

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SegmentIQ — Customer Intelligence Platform

localhost:5173/segmentation

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K-Means **Hierarchical** **DBSCAN**

Number of Clusters (k) **4** Silhouette: 0.31 Customers clustered: 1,000
2 10

Silhouette Score per K
Higher = better-defined clusters

Cluster Summary
RFM averages per cluster

Cluster	Size	Avg Recency	Avg Frequency	Avg Monetary £
Cluster 0	1,204	27.5d	3.5	£1151
Cluster 1	1,257	33d	18.7	£10448
Cluster 2	1,884	375.5d	1.4	£324
Cluster 3	1,533	262d	4.3	£1706

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SegmentIQ — Customer Intelligence Platform

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Customer Segmentation
UCI Online Retail II - Real ML Analysis

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Customer Segmentation
Real RFM features from UCI Online Retail II — 4K+ customer profiles

Number of Clusters: 4

K-Means Hierarchical DBSCAN

Dendrogram
Hierarchical cluster merging tree (Ward linkage, sample of 500 customers)

Cluster Scatter (PCA 2D)
Agglomerative clusters projected to 2D

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Customer Segmentation
UCI Online Retail II - Real ML Analysis

Backend: localhost:8000

Customer Segmentation
Real RFM features from UCI Online Retail II — 4K+ customer profiles

Number of Clusters: 4

Cluster Summary
RFM averages for each hierarchical cluster

Cluster	Size	Avg Recency	Avg Frequency	Avg Monetary £
Cluster 0	1,627	68d	15.8	£8720
Cluster 1	1,493	288.5d	1.5	£396
Cluster 2	901	19.5d	4.4	£1485
Cluster 3	1,857	336.3d	2.7	£877

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SegmentIQ — Customer Intelligence Platform

localhost:5173/segmentation

Customer Segmentation
UCI Online Retail II - Real ML Analysis

Customer Segmentation
Real RFM features from UCI Online Retail II — 4K+ customer profiles

Epsilon (ϵ) Min Samples
Clusters: 3 Noise Points: 269 Noise Rate: 4.58%

DBSCAN Cluster Scatter
Red points are noise/anomalies (ϵ -neighborhood too sparse)

Cluster & Noise Summary
Including anomaly/noise group (cluster = -1)

Label	Size	Avg Recency	Avg Frequency	Avg Monetary
Noise	269	116d	26.6	£25442
Cluster 0	4,018	144.4d	7	£2587
Cluster 1	1,584	361.1d	1	£318
Cluster 2	7	3d	1	£230

Backend: localhost:8000

Dashboard Segmentation Dim. Reduction Market Basket Reports

K-Means Hierarchical DBSCAN

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SegmentIQ — Customer Intelligence Platform

localhost:5173/dimensionality

Dimensionality Reduction
UCI Online Retail II - Real ML Analysis

Dimensionality Reduction
Visualize high-dimensional customer space in 2D & 3D

PC1 Explained Variance: 58.5% Cumulative: 58.5%
PC2 Explained Variance: 20.2% Cumulative: 78.7%
PC3 Explained Variance: 12.1% Cumulative: 90.8%

PCA 2D Projection
Customers plotted on first two principal components, colored by K-Means cluster

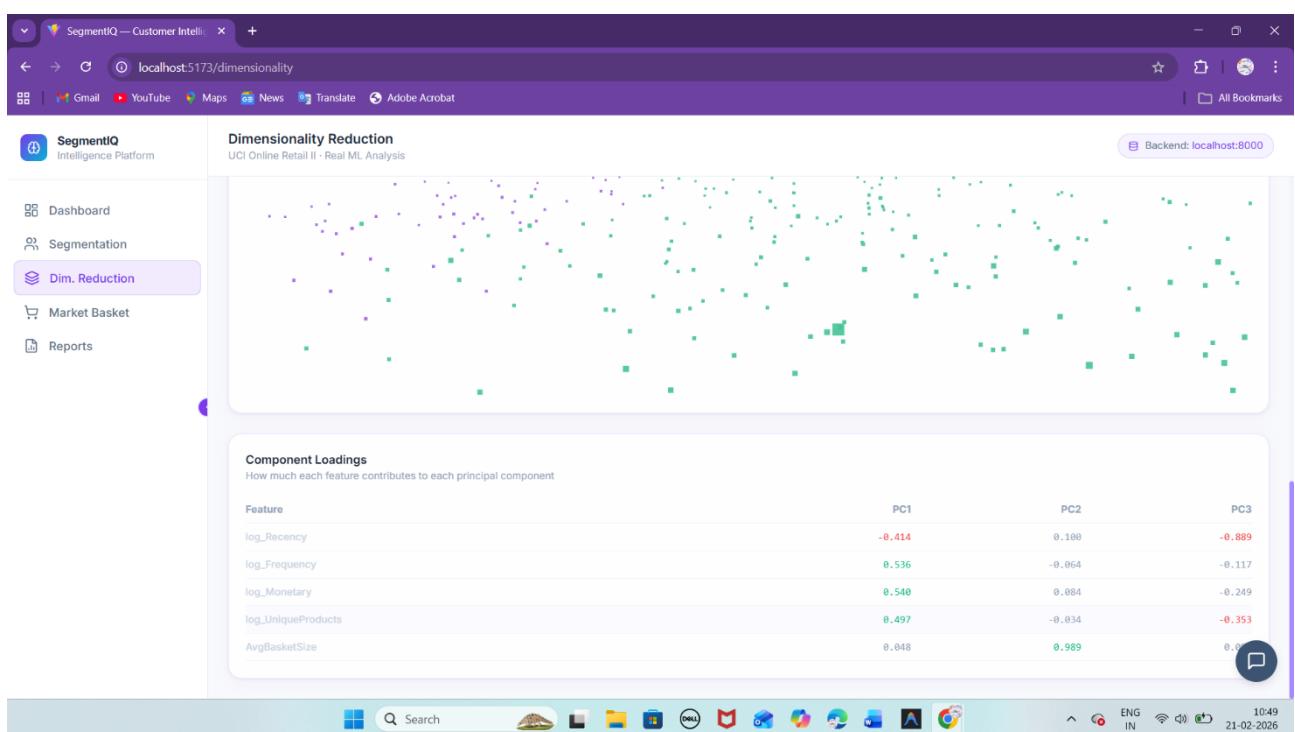
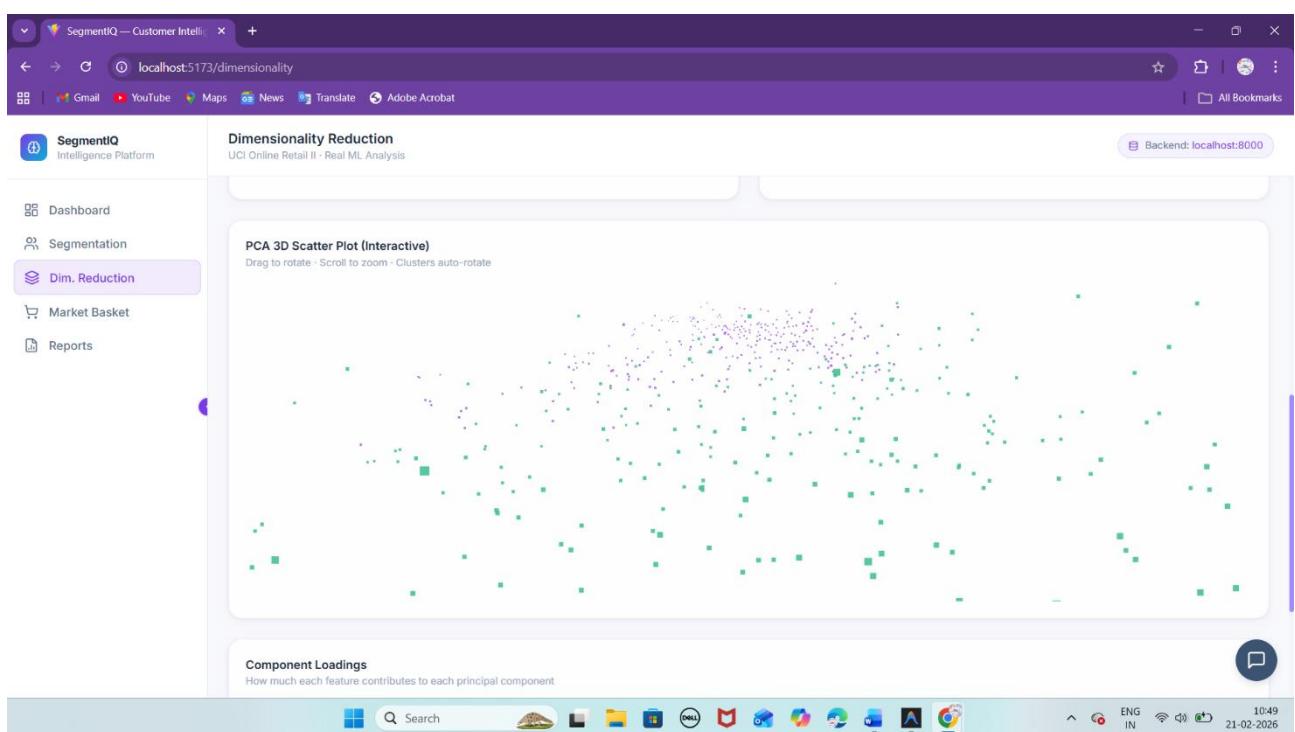
Explained Variance Ratio
Variance captured by each principal component

Backend: localhost:8000

Dashboard Segmentation Dim. Reduction Market Basket Reports

PCA LDA

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SegmentIQ — Customer Intelligence Platform

localhost:5173/dimensionality

Dimensionality Reduction
UCI Online Retail II - Real ML Analysis

Dimensionality Reduction
Visualize high-dimensional customer space in 2D & 3D

LDA 2D Projection
Fisher's Linear Discriminant — maximizes class separability

Linear Discriminant Analysis (LDA) finds the projection that **maximizes between-class variance** and minimizes within-class variance — giving better class separation than PCA.

Labels: K-Means (k=4) cluster labels used as class targets
Components: 2 discriminant axes

PCA Unsupervised - Max variance - Global structure
LDA Supervised - Max separability - Class boundaries

LDA Discriminant Variance

LD1	51.9%
LD2	47.0%

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SegmentIQ — Customer Intelligence Platform

localhost:5173/market-basket

Market Basket Analysis
Apriori algorithm on real invoice transactions — top 50 products

Frequent Itemsets: 82 Total Rules: 49

Market Basket Analysis
Apriori algorithm on real invoice transactions — top 50 products

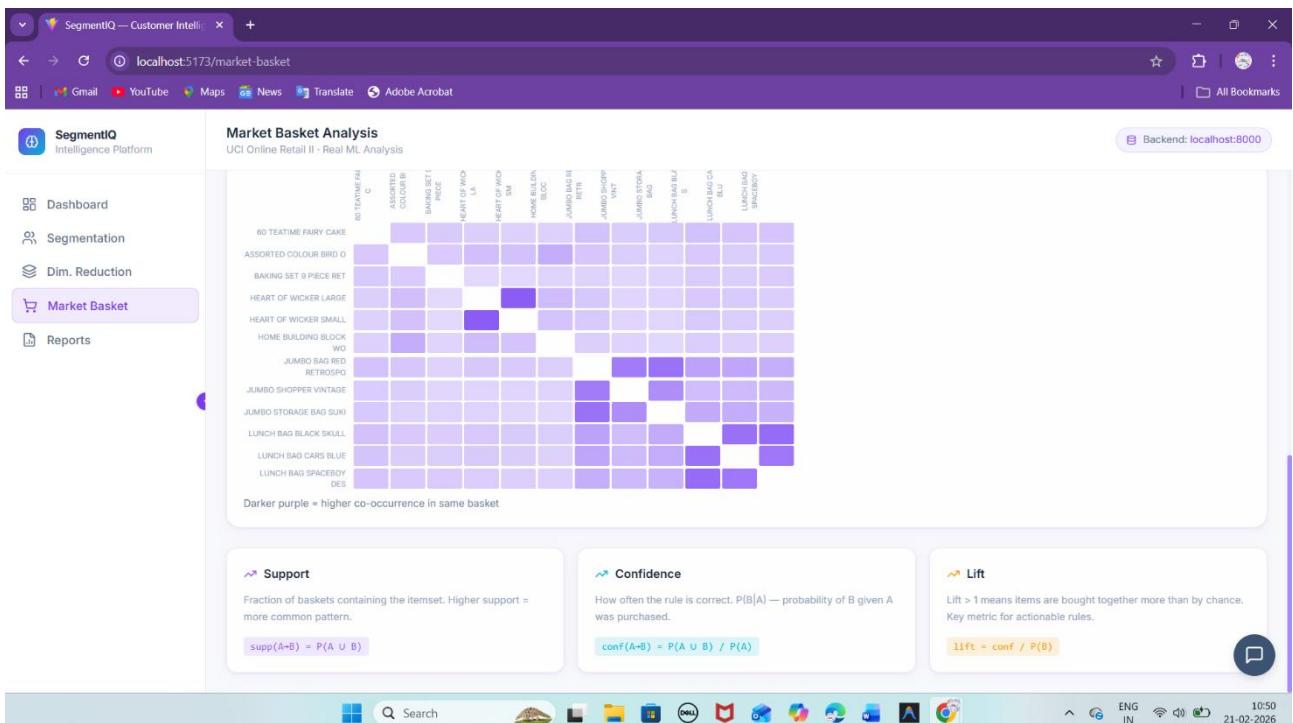
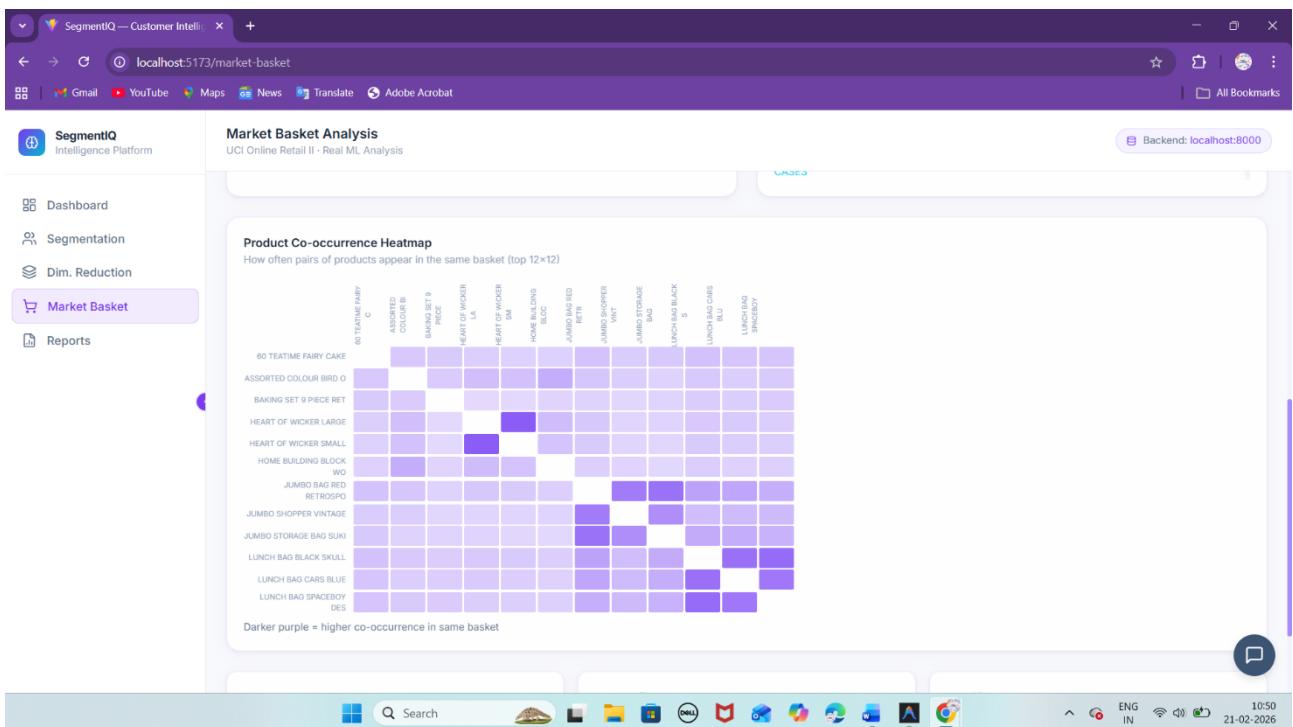
Min Support: 0.02 Min Confidence: 0.3

Top 20 Products by Purchase Frequency
Most frequently purchased items in the real dataset

Top Association Rules (by Lift)
Rules with highest lift indicate strongest product relationships

Antecedent → Consequent	Support	Conf	Lift
STRAWBERRY CERAMIC TRINKET BOX → SWEETHEART CERAMIC TRINKET BOX	0.0311	0.4494	10.0836
SWEETHEART CERAMIC TRINKET BOX → STRAWBERRY CERAMIC TRINKET BOX	0.0311	0.6977	10.0836
GIN + TONIC DIET METAL SIGN → COOK WITH WINE METAL SIGN	0.022	0.4166	8.9358
COOK WITH WINE METAL SIGN → GIN + TONIC DIET METAL SIGN	0.022	0.471	8.9358
WOODEN PICTURE FRAME WHITE FINISH → WOODEN FRAME ANTIQUE WHITE	0.0378	0.5989	8.8756
WOODEN FRAME ANTIQUE WHITE → WOODEN PICTURE FRAME WHITE FINISH	0.0378	0.5601	8.8756
CHOCOLATE HOT WATER BOTTLE → HOT WATER BOTTLE TEA AND	0.0236	0.4285	8.6734

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SegmentIQ — Customer Intelligence Platform

localhost:5173/reports

Backend: localhost:8000

Cluster Reports & Insights

UCI Online Retail II - Real ML Analysis

Number of Clusters (k) 2 8

- High-Value Occasional Cluster 0** 20.5% 1,204 customers

Spend a lot but purchase infrequently.

Campaign Strategy
Target with premium products and curated collections.
- Loyal Customer Cluster 1** 21.4% 1,257 customers

Frequent buyers with consistent spend.

Campaign Strategy
Upsell higher-value products, ask for reviews and referrals.
- Lost Customer Cluster 2** 32.1% 1,884 customers

Long inactive — haven't purchased in months.

Campaign Strategy
Reactivation campaigns with aggressive discounts.
- Lost Customer Cluster 3** 26.1% 1,533 customers

Long inactive — haven't purchased in months.

Campaign Strategy
Reactivation campaigns with aggressive discounts.

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SegmentIQ — Customer Intelligence Platform

localhost:5173/reports

Backend: localhost:8000

Business Intelligence Summary

Consolidated cluster report with revenue potential per segment

Persona	Customers	Share	Avg Recency	Avg Frequency	Avg Spend £	Revenue Potential
High-Value Occasional	1,204	20.5%	27.5d	3.5	£1151	£1385K
Loyal Customer	1,257	21.4%	33d	18.7	£10448	£13133K
Lost Customer	1,884	32.1%	375.5d	1.4	£324	£610K
Lost Customer	1,533	26.1%	262d	4.3	£1706	£2616K
Total	5,878	100%				£17743K

Retain Champions
Invest in VIP loyalty programs and early-access campaigns for your highest-value customers. Churn here is costliest.

Win Back At-Risk
Trigger personalized re-engagement emails with time-limited discounts for customers who haven't purchased in 60+ days.

Upsell Loyals
Loyal customers are prime candidates for bundle offers and premium product recommendations to increase basket size.

Onboard New Customers
A structured onboarding journey with welcome offers and product discovery emails can convert new customers to loyalists.

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FILE STRUCTURE:

The screenshot shows the Antigravity IDE interface with the following details:

- File Explorer:** On the left, it displays the project structure under "CustomerSegmentation". The "src" folder contains "frontend", "public", and "ui" subfolders. "ui" contains "charts", "three", and "ui" (which further contains "ChartCard.jsx", "SliderControl.jsx", "StatCard.jsx", "TabSwitcher.jsx", "Navbar.jsx", and "Sidebar.jsx"). "hooks", "layouts", and "pages" are also listed.
- Code Editor:** The main area shows the content of "App.jsx". The code defines a functional component "App" that returns a `<BrowserRouter>` component. Inside, it uses `<AnimatePresence mode="wait">` to manage components. It has a `<Routes>` block with five `<Route>` entries: "/dashboard", "/segmentation", "/dimensionality", "/market-basket", and "/reports". Each route points to a specific component like `<Dashboard />`, `<Segmentation />`, etc.
- Terminal:** At the bottom, the terminal window shows the command `PS D:\CustomerSegmentation\frontend> npm run dev` and the output: `> Frontend@0.0.0 dev` and `> vite`. Below this, VITE version information is shown: `VITE v7.3.1 ready in 2837 ms`, followed by local and network URLs: `→ Local: http://localhost:5173/` and `→ Network: http://10.118.159.152:5173/`.
- Bottom Bar:** Includes tabs for "Outline", "Timeline", and "Search". The status bar at the bottom right shows "Line 1, Col 1", "Spaces: 2", "UTF-8", "LF", "JavaScript/TSX", "Antigravity - Settings", and language codes "ENG IN".

Conclusion:

SegmentIQ demonstrates how unsupervised machine learning can transform raw e-commerce transaction data into structured, actionable business intelligence. By combining clustering algorithms, dimensionality reduction, and association rule mining within a full-stack interactive dashboard, the platform enables automated customer segmentation and strategic marketing decision-making.

The modular and scalable architecture allows integration with new datasets, additional machine learning models, and cloud deployment, making SegmentIQ a practical and extensible analytics solution for modern e-commerce businesses.