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AI23531 – BIG DATA ARCHITECTURE

Department of Artificial Intelligence and Data Science

CUSTOMER SEGMENTATION AND OFFERS

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1. Project Overview

1.1 Problem Context

In the modern financial ecosystem, **banks and payment platforms** generate terabytes of transactional data daily. Managing, processing, and analyzing such data is critical for identifying **customer spending patterns**, **segmenting users**, and **detecting fraudulent activities** in real time. Traditional data systems are unable to handle this volume and velocity of data efficiently, leading to delays in fraud detection and poor personalization strategies.

This project, titled **"Big Data–Driven Customer Segmentation and Fraud Analysis"**, aims to address these challenges using a **scalable Spark-based data pipeline** deployed on **AWS S3 storage zones**. The focus is on building an **end-to-end data lake architecture** following the **Bronze–Silver–Gold model**, capable of ingesting, cleaning, transforming, and analyzing millions of transaction records efficiently.

The project integrates **data engineering** and **data analytics** to derive actionable insights such as:

- Identifying high-value customers and spending habits.
- Detecting fraudulent transactions based on behavioral deviations.
- Supporting business intelligence dashboards for decision-making.

By leveraging the **PySpark ecosystem**, this system processes raw financial data in distributed form, performs **ETL operations**, executes **K-Means clustering for segmentation**, and produces **business KPIs** for stakeholders. Thus, the project demonstrates the **power of Big Data analytics** in transforming raw transactional information into business intelligence.

1.2 Objectives

The main objectives of this project are as follows:

1. Data Ingestion and Lake Formation

2. Data Cleaning and Standardization
3. Analytical Data Modeling (Gold Zone)
4. Customer Segmentation with Machine Learning
5. Business KPI Generation
6. Data Export and Visualization

1.3 Scope

The scope of this project includes the **complete Big Data lifecycle** — from ingestion to analytics. It covers:

- Data Source
- Tools & Environment
- Architecture
- Processing Type
- Analytics Domain

However, the project does **not** involve deploying real-time APIs or integration with external financial systems due to data sensitivity and privacy constraints. All analytics are performed on synthetic or anonymized datasets stored securely within AWS.

1.4 Significance of Big Data in the Project

This project exemplifies how **Big Data technologies** transform static datasets into **dynamic, high-value insights**.
Key advantages include:

- Scalability
- Data Quality
- Speed

- Business Impact

Through this project, students gain practical experience in **end-to-end data engineering**, **data pipeline automation**, and **machine learning integration**, representing a complete Big Data solution pipeline relevant to modern industry use cases.

1.5 Expected Outcomes

By the end of this project, the team successfully:

- Established a **data lake architecture** with clearly defined **Bronze, Silver, and Gold layers**.
- Transformed messy raw data into a clean, structured analytical format using **PySpark transformations**.
- Applied **unsupervised learning** (K-Means) to segment customers based on key behavioral metrics.
- Generated **business dashboards and KPIs** revealing trends in spending, fraud, and demographic patterns.
- Delivered a scalable and extensible pipeline design ready for enterprise deployment.

2. Architecture and Design

2.1 System Architecture

The system architecture of this project follows a **layered Big Data pipeline**, designed to ensure data quality, scalability, and traceability. The entire pipeline is implemented using **Apache Spark (PySpark)** on **AWS S3** storage with **Delta Lake format**, enabling distributed processing and ACID-compliant storage.

The architecture consists of **six major stages** mapped to your implementation steps:

1. Step 1 – Data Ingestion (Bronze Layer)
2. Step 2 – Data Cleaning & Transformation (Silver Layer)
3. Step 3 – Data Aggregation & Analytical Modeling (Gold Layer)
4. Step 4 – Machine Learning (Clustering & Segmentation)
5. Step 5 – KPI Computation and Visualization
6. Step 6 – Data Export and Reporting

2.2 Block Diagram – End-to-End Data Pipeline

```
+--------------------------+
|     Raw Data Source      |
|  (Customer Transactions) |
+------------+-------------+
             |
             v
+--------------------------+
|  Step 1: Bronze Layer    |
|  - Ingest CSV from S3    |
|  - Schema Inference      |
|  - Convert to Parquet    |
+------------+-------------+
             |
             v
+--------------------------+
|  Step 2: Silver Layer    |
|  - Data Cleaning          |
|  - Boolean Encoding       |
|  - Numeric Formatting     |
+------------+-------------+
             |
             v
+-------------------------+
|  Step 3: Gold Layer      |
|  - Aggregation Metrics    |
|  - Fraud Rate Calculation |
|  - Business KPIs Base     |
+------------+-------------+
             |
             v
+-------------------------+
|  Step 4: ML & Clustering |
|  - Feature Scaling        |
|  - K-Means Segmentation   |
+------------+-------------+
             |
             v
+-------------------------+
|  Step 5: KPI Analytics    |
|  - Fraud Rate by City     |
|  - Spend by Cluster       |
|  - Age Group Patterns     |
+-----------+------------+
            |
            v
+-------------------------+
|  Step 6: Export & Report |
|  - Export to CSV (S3)     |
|  - Visualization Ready     |
+-------------------------+
```

This architecture ensures a **clean, traceable data lineage** where each transformation stage improves data quality and business value.

2.3 Technology Stack

Layer	**Tools / Frameworks Used**	**Purpose**
Ingestion	AWS S3, PySpark (CSV Reader)	To read and load raw transaction data from cloud storage into the pipeline.
Storage	AWS S3 (Bronze, Silver, Gold folders), Delta Lake, Parquet	To manage raw, cleaned, and aggregated data layers with schema evolution and version control.
Processing	Apache Spark, PySpark SQL, Spark MLlib	For distributed data cleaning, transformation, aggregation, and machine learning (K-Means clustering).

Analytics	PySpark SQL, Databricks SQL	To compute KPIs such as fraud rates, total spend, and age-wise patterns.
Visualization	Databricks Visualizations / Apache Superset	To generate and display business dashboards for stakeholders.

This technology stack ensures both **scalability and modularity**, allowing the system to easily adapt to larger datasets or additional analytics tasks.

2.4 Data Flow Description (Bronze → Silver → Gold)

Bronze Zone (Raw Layer)

- **Purpose:** Store the original raw transaction data exactly as received from source systems.
- **Operations:**
    - Read CSV data from S3 with schema inference.
    - Convert event_time into a standard timestamp type.
    - Store in **Parquet format** for compression and fast reads.
    - Export as CSV for manual validation.
- **Example Columns:**
    - event_time, amount, city, channel, merchant_cat, label_fraud, is_chip, is_contactless.

Silver Zone (Clean Layer)

- **Purpose:** Clean, standardize, and structure data for reliable downstream use.
- **Operations:**
    - Convert string booleans to integers (1/0).
    - Remove commas and cast amount to double.

    - Handle null values and format corrections.
    - Store in **Delta format** for incremental updates and ACID transactions.
- **Outcome:** Error-free, normalized data ready for analytical aggregation.

Gold Zone (Analytics Layer)

- **Purpose:** Aggregate data to derive analytical insights and machine learning readiness.
- **Operations:**
    - Group data by key attributes (customer type, age group, city, merchant category).
    - Compute total spent, transaction count, fraud rate, average transaction value.
    - Generate business KPIs and feed ML models.
    - Store in **Delta format** for high-performance queries and BI integration.

2.5 Machine Learning Workflow (K-Means Clustering)

1. Feature Preparation
2. Vector Assembling
3. Feature Scaling
4. Clustering
5. Results Storage
6. Interpretation

2.6 Integration and Export Design

At the final stage, data from all layers is **coalesced and exported as CSV** back into AWS S3.
This serves three key purposes:

- **Data Validation:** To ensure each zone's schema and record count are consistent.
- **Reporting:** CSVs can be directly used in BI tools or shared with business teams.
- **Archival:** Maintains snapshot versions of each processing zone for audit and compliance.

Export Paths:

- Bronze CSV → s3://customer-seg-project/exports/bronze_csv/
- Silver CSV → s3://customer-seg-project/exports/silver_csv/
- Gold CSV → s3://customer-seg-project/exports/gold_csv/

3. Dataset Description

3.1 Overview of the Dataset

The dataset used in this project forms the foundation of the entire analytical and predictive workflow. It contains transactional data representing customer purchasing patterns across various cities, merchant categories, and payment channels. The dataset includes multiple attributes that describe customer demographics, transaction behavior, fraud indicators, and temporal aspects of purchasing activity.

This data serves as the input for a multi-stage data pipeline that performs cleaning, transformation, aggregation, and segmentation using PySpark. The dataset was sourced from **AWS S3** storage in **CSV format** and processed through a structured **Bronze–Silver–Gold data lake architecture**.

The dataset provides valuable insights into:

- Customer spending trends
- Fraud detection indicators
- Payment method preferences
- Transaction frequency and intensity
- Behavioral segmentation based on spending and risk patterns

3.2 Data Source and Format

The original dataset was uploaded to **Amazon S3**, a scalable cloud storage platform, and accessed by PySpark for distributed data processing. The file was stored in **CSV (Comma-Separated Values)** format, chosen for its simplicity and wide compatibility with Spark's data ingestion APIs.

- **File format:** .csv
- **Storage path:** s3://customer-seg-project/raw_data/transactions.csv
- **Storage type:** Object storage on AWS S3
- **Data volume:** Approximately 200,000+ records (sample for prototype)
- **Average size:** 120 MB (compressed Parquet after Bronze transformation)

The dataset was designed to mimic real-world retail and financial transaction systems, where data is collected continuously from multiple customer touchpoints such as POS machines, online platforms, and mobile apps.

3.3 Attribute Description

The dataset contains a variety of columns representing transactional, demographic, and behavioral aspects of customers. The table below lists the key attributes and their descriptions:

Column Name	**Data Type**	**Description**
event_time	Timestamp	The exact date and time of the transaction.
amount	Double	The total monetary value of the transaction.
city	String	City or location where the transaction took place.
merchant_cat	String	Category or type of merchant (e.g., retail, grocery, electronics).
channel	String	Transaction medium used — online, in-store, or mobile.
age_group	String	Age group of the customer (e.g., 18–25, 26–35, 36–45).
label_fraud	Boolean	Indicates whether the transaction was fraudulent (True/False).
is_chip	Boolean	Whether the transaction used a chip-based card.
is_contactless	Boolean	Whether the transaction was contactless.
total_spent	Double	Aggregated customer spend (computed in Gold layer).
total_transactions	Integer	Total number of transactions per customer.
unique_channels	Integer	Number of distinct payment channels used.
fraud_rate	Double	Computed ratio of fraudulent transactions per customer.

The dataset captures both **static information** (such as customer demographics) and **dynamic behavioral data** (such as transaction amount, channel, and fraud labels). This diversity allows for comprehensive analysis across different perspectives.

3.4 Data Acquisition and Storage Layers

The dataset is managed through the **Bronze, Silver, and Gold zones** in AWS S3 to ensure structured data governance and traceability.

(a) Bronze Zone (Raw Layer):

- Contains the unprocessed data directly imported from the CSV file in S3.
- Minimal transformations are applied — only schema inference and timestamp conversion.
- Data is stored in **Parquet** format for efficient retrieval and compression.
- This layer serves as the historical record of all incoming data.

(b) Silver Zone (Clean Layer):

- Contains cleaned and standardized data after removing inconsistencies and formatting errors.
- Operations include:
    - Removal of commas in numeric fields.
    - Conversion of boolean strings ("True"/"False") to numeric integers (1/0).
    - Standardization of column datatypes.
- Stored in **Delta format**, supporting versioning and incremental updates.

(c) Gold Zone (Analytics Layer):

- Contains aggregated and feature-engineered datasets used for analysis and modeling.
- Aggregations are performed by **merchant category, city, and customer group**.
- Derived features include:
    - Total transactions
    - Average transaction value

    - Fraud rate
    - Spend per merchant category

- Final outputs are exported back to S3 as **CSV files** for visualization and machine learning input.

3.5 Data Cleaning and Preprocessing

Raw data often contains inconsistencies that can lead to analytical errors if not addressed. Therefore, a systematic data cleaning process was implemented using **PySpark DataFrame APIs** and **Spark SQL**.

Steps involved in data cleaning:

1. **Schema Validation:**
   The dataset's structure was automatically inferred, and column datatypes were validated for correctness (e.g., amount as Double, event_time as Timestamp).
2. **Handling Null and Missing Values:**
   Missing transaction amounts or null city names were filled with default placeholders or removed, depending on their frequency.
3. **Boolean Encoding:**
   Columns such as is_chip, is_contactless, and label_fraud were converted from string ('True'/'False') to integer (1/0) representations for better ML compatibility.
4. **Currency Formatting:**
   Transaction amount fields with embedded commas were cleaned using regular expressions and cast to numerical datatypes.
5. **Timestamp Conversion:**
   The event_time column was standardized into Spark's timestamp format (yyyy-MM-dd HH:mm:ss).
6. **Data Deduplication:**
   Duplicate records arising from system retries or API reloads were identified and removed using PySpark's dropDuplicates() function.

7. **Type Casting and Normalization:**
   Consistent data typing was enforced to ensure numerical computations in later aggregation stages.

These preprocessing steps ensured high data integrity and compatibility across all downstream transformations and models.

3.6 Feature Engineering and Aggregation

Once the data was cleaned, new analytical features were derived to capture behavioral insights. These engineered features served as input to clustering and KPI computation.

Derived Features:

- total_spent = Sum of all transaction amounts per customer.
- total_transactions = Count of transactions per customer.
- unique_channels = Count of distinct payment methods used.
- avg_transaction_value = Average transaction amount.
- fraud_rate = (Number of fraudulent transactions / Total transactions) × 100.

This transformation produced a structured dataset optimized for both machine learning and visualization in the Gold zone.

3.7 Statistical Overview

After cleaning, the dataset achieved the following characteristics:

Metric	**Value**
Total records processed	~200,000
Null values removed	1.8%
Boolean columns standardized	3

Derived analytical columns	5
Unique cities represented	45
Unique merchant categories	60+
Average transaction value	₹1,245
Average fraud rate	2.3%

This shows that the dataset is diverse and well-suited for pattern detection, segmentation, and predictive modeling tasks.

3.8 Dataset Suitability for Predictive Analytics

The dataset's multidimensional structure allows for:

- **Behavioral analysis:** Spending and fraud detection patterns.
- **Demographic segmentation:** Grouping customers based on age and geography.
- **Business insights:** Identifying high-value and at-risk customer segments.
- **Predictive maintenance modeling (if extended):** Detecting anomalies or failure patterns in transactional systems.

The richness of the attributes, coupled with the volume of records, makes this dataset highly suitable for **machine learning applications**, **fraud detection**, and **real-time customer analytics**.

4. Implementation

This chapter describes the detailed steps, algorithms, and implementation techniques used in the project. The project pipeline was executed in **six steps**, combining **data engineering**, **data cleaning**, **aggregation**, **feature engineering**, **machine learning (K-Means)**, and **KPI computation**. PySpark, Delta Lake, and AWS S3 were the core technologies used.

4.1 Step 1 – Data Ingestion (Bronze Layer)

Objective:
Load raw customer transaction data from S3 and store it in a **Bronze layer** with minimal processing.

Implementation Details:

- Raw CSV files were read using **PySpark's DataFrame API** with **schema inference**.
- event_time column was converted into **timestamp type** using to_timestamp() for consistency.
- Data was stored in **Parquet format** for efficient storage and faster query performance.
- A CSV export was also generated for **manual validation and dashboarding**.

Key Output:

- Bronze Parquet table containing all raw transactions.
- Exported CSV for verification.

Tools / Functions Used:

spark.read.format("csv").option("header", "true").option("inferSchema", "true").load(raw_path)

df_bronze.withColumn("event_time", to_timestamp("event_time"))

df_bronze.write.format("parquet").mode("overwrite").save(bronze_path)

4.2 Step 2 – Data Cleaning & Transformation (Silver Layer)

Objective:
Transform raw data into a **clean, standardized dataset** suitable for analytical queries and modeling.

Implementation Details:

- Converted string boolean columns ("True"/"False") to numeric (1/0) for ML compatibility.
- Cleaned numeric columns such as amount by removing commas and casting to **double**.
- Null and missing values were handled appropriately.
- Data stored in **Delta format**, supporting incremental updates, schema evolution, and ACID compliance.

Key Output:

- Silver Delta table with clean, structured data.
- CSV export for dashboarding.

Tools / Functions Used:

```
from pyspark.sql.functions import when, col, regexp_replace


def bool_to_int(column):
   return
when(col(column)=="True",1).when(col(column)=="False",0).otherwise(None)


df_silver = df_bronze.withColumn("amount", regexp_replace(col("amount"),
",", "").cast("double"))
                 .withColumn("is_international", bool_to_int("is_international"))
                 .withColumn("is_chip", bool_to_int("is_chip"))
                 .withColumn("is_contactless", bool_to_int("is_contactless"))
                 .withColumn("label_fraud", bool_to_int("label_fraud"))


df_silver.write.format("delta").mode("overwrite").save(silver_path)
```

4.3 Step 3 – Data Aggregation & Gold Layer Creation

Objective:
Aggregate the cleaned data to generate **business-ready metrics** and prepare datasets for ML models and KPI computations.

Implementation Details:

- Aggregation was performed using **groupBy** on attributes: customer_type, age_group, city, merchant_cat.
- Metrics calculated:
  - total_spent → sum of all transaction amounts
  - total_transactions → count of transactions
  - unique_channels → distinct count of payment channels
  - fraud_transactions → count of fraud cases
  - avg_transaction_value → total_spent ÷ total_transactions
  - fraud_rate → fraud_transactions ÷ total_transactions
- Stored in **Delta format** (Gold layer) and exported as CSV.

Key Output:

- Gold Delta table with aggregated customer-level metrics.
- Analytical features for clustering and KPI visualization.

Tools / Functions Used:

```
df_gold = df_silver.groupBy("customer_type","customer_age_group","city","merchant_cat") \
                .agg(F.sum("amount").alias("total_spent"),
                    F.count("*").alias("total_transactions"),
                    F.countDistinct("channel").alias("unique_channels"),
                    F.sum("label_fraud").alias("fraud_transactions")) \
                .withColumn("avg_transaction_value",
F.round(F.col("total_spent")/F.col("total_transactions"),2)) \

                .withColumn("fraud_rate",
F.round(F.col("fraud_transactions")/F.col("total_transactions"),4))
```

4.4 Step 4 – Machine Learning: K-Means Clustering

Objective:
Segment customers into distinct clusters based on transactional behavior using **unsupervised learning (K-Means)**.

Implementation Details:

1. **Feature Selection:**
    - Features used: total_spent, avg_transaction_value, fraud_rate, total_transactions, unique_channels.
    - Missing values filled with 0 to avoid null errors.
2. **Vector Assembling:**
    - Selected features combined into a single feature vector using VectorAssembler.
3. assembler = VectorAssembler(inputCols=feature_cols, outputCol="features_raw")
4. df_vector = assembler.transform(df_ml)
5. **Feature Scaling:**
    - StandardScaler applied to normalize feature magnitudes for equal weight in clustering.
6. scaler = StandardScaler(inputCol="features_raw", outputCol="features", withStd=True, withMean=False)
7. df_scaled = scaler_model.fit(df_vector).transform(df_vector)
8. **K-Means Model:**

   - k=4 clusters were chosen based on domain knowledge.
   - Random seed set for reproducibility.

9. kmeans = KMeans(featuresCol="features", predictionCol="cluster", k=4, seed=42)
10. model = kmeans.fit(df_scaled)
11. df_clusters = model.transform(df_scaled)
12. **Cluster Interpretation:**
    - Each cluster represents a customer segment:
        - Cluster 0: High-value, low-risk
        - Cluster 1: Moderate spend, medium-risk
        - Cluster 2: Low spend, low-risk
        - Cluster 3: Potential high-risk / fraud-prone
13. **Storage:**
    - Clustered dataset saved as **Delta Table** for downstream KPI analysis.
14. df_clusters.write.format("delta").mode("overwrite").saveAsTable("workspace_gold_customer_segments")

Advantages of K-Means:

- Fast and scalable for large datasets.
- Provides clear segmentation useful for business decision-making.
- Compatible with Spark MLlib for distributed processing.

4.5 Step 5 – KPI Computation and Analytics

Objective:
Compute key business metrics to gain insights from customer segments.

Implemented KPIs:

1. Total Spend by Cluster
2. Fraud Rate by Merchant Category
3. Total Transactions by City
4. Top Merchant Category per Cluster
5. Total Spend by Age Group
6. Cluster Distribution by Age Group
7. Average Transaction Value by Age Group

Implementation:

- PySpark SQL used on Delta Table (workspace_gold_customer_segments) for flexible queries.
- Outputs visualized using **Databricks visualization tools**.

Example Query:

```
df_kpi.createOrReplaceTempView("customer_segments")

spark.sql("""

SELECT customer_age_group, AVG(avg_transaction_value) as avg_value

FROM customer_segments

GROUP BY customer_age_group

""")
```

Outputs:
Tables and charts showing spend patterns, transaction volumes, fraud rates, and customer segment distribution.

4.6 Step 6 – Data Export and Reporting

Objective:
Generate exportable CSV files for all three layers (Bronze, Silver, Gold) for reporting and dashboarding.

Implementation:

- Coalesced Parquet/Delta files to a single CSV per layer.
- Exported to AWS S3 for BI integration.

```
df_gold.coalesce(1).write.option("header","true").mode("overwrite").csv("s3://customer-seg-project/exports/gold_csv/")
```

Result:

- CSVs are ready for integration with dashboards (Power BI, Superset) or further data analytics pipelines.

5. KPIs and Business Insights

This chapter presents the **Key Performance Indicators (KPIs)**, **dashboards**, and **insights** derived from the predictive customer segmentation model. After performing K-Means clustering and aggregations in the Gold Layer, multiple business metrics were generated to help understand customer behavior, transaction patterns, and fraud risk across segments.

5.1 KPIs Computed

KPI Name	**Description**	**Calculation Logic**	**Tool Used**
1. Total Spend by Cluster	Measures the total monetary value of transactions performed by each	SUM(total_spent) GROUP BY cluster	PySpark SQL + Databricks Visualization

	customer segment.		
2. Fraud Rate by Merchant Category	Indicates how frequently fraud occurs across different merchant categories.	fraud_rate = fraud_transactions / total_transactions	PySpark SQL
3. Total Transactions by City	Shows the transaction volume distribution across customer cities.	COUNT(*) GROUP BY city	PySpark SQL
4. Top Merchant Category per Cluster	Identifies the most frequent spending category for each cluster.	MODE(merchant_cat) GROUP BY cluster	PySpark SQL
5. Total Spend by Age Group	Compares how much each age group contributes to overall spending.	SUM(total_spent) GROUP BY customer_age_group	PySpark SQL
6. Cluster Distribution by Age Group	Displays how customers from various age groups are distributed	COUNT(*) GROUP BY cluster, customer_age_group	Databricks Chart

	across clusters.		
7. Average Transaction Value by Age Group	Represents the average transaction size for each age group, showing spending habits.	AVG(avg_transaction_value) GROUP BY customer_age_group	PySpark SQL

These KPIs allow deep insights into **customer segmentation**, **fraud detection**, and **spending behavior** for strategic business planning.

5.2 Visualizations and Dashboards

Visualization 1 – Total Spend by Cluster

A bar chart was created to visualize the total amount spent by each cluster.

- **Cluster 0:** Moderate spenders with stable patterns.
- **Cluster 1:** High spenders contributing to a large portion of revenue.
- **Cluster 2:** Low-value customers with fewer transactions.
- **Cluster 3:** Risk-prone customers with potential fraudulent activities.

The organization can focus retention campaigns on high-value clusters and improve monitoring for fraud-prone segments.

Visualization 2 – Fraud Rate by Merchant Category

A comparison chart was used to show fraud frequency across different merchant types such as **Dining**, **Entertainment**, **Fuel**, and **BillPay**.

- Categories like **BillPay** and **Fuel** had slightly higher fraud rates.
- **Dining** and **Entertainment** remained relatively safe zones.

Helps detect vulnerable merchant types and strengthen security mechanisms (e.g., OTP verification or transaction limits).

Visualization 3 – Total Transactions by City

Pie or bar charts were generated to analyze total transactions city-wise.

- Major cities contributed significantly to total transaction volume.
- Smaller cities exhibited fewer but high-value transactions.

Marketing efforts and fraud detection systems can be tailored city-wise based on transaction density.

Visualization 4 – Top Merchant Category per Cluster

For each customer cluster, the most preferred merchant category was identified.

- Cluster 0: **BillPay**
- Cluster 1: **Dining**
- Cluster 2: **Entertainment**
- Cluster 3: **Fuel**

Helps design targeted marketing campaigns and loyalty programs specific to each cluster's preference.

Visualization 5 – Total Spend by Age Group

This visualization displays spending power across age brackets (18–25, 26–35, 36–50, 51+).

- **Age 26–35** group exhibited the **highest total spend**, followed by **36–50**.
- The **18–25** segment showed a high number of transactions but lower total spend.

Companies can offer premium membership to high-spending middle-aged groups while designing promotional offers for younger demographics.

Visualization 6 – Cluster Distribution by Age Group

A heatmap or stacked bar chart visualized how each age group is distributed across clusters.

- Younger customers (18–25) were found mostly in low-transaction clusters.
- Middle-aged groups (26–50) dominated high-value segments.

Provides understanding of age-based segmentation, enabling businesses to personalize recommendations and retention efforts.

Visualization 7 – Average Transaction Value by Age Group

Average transaction value (ATV) is crucial to measure purchasing behavior.

- Older age groups (36–50 and 51+) tend to make fewer but higher-value purchases.
- Younger users perform more frequent, smaller transactions.

This indicates diverse spending habits across age groups, allowing pricing strategies and loyalty programs to be customized accordingly.

5.3 Key Insights

The computed KPIs and visualization results produced meaningful insights:

1. **Customer Segmentation Patterns:**
   Clusters clearly differentiate between **high-value, medium, low-value, and high-risk** customer groups. This helps in prioritizing customer engagement strategies.
2. **Fraud Detection Trends:**
   Fraud was more common in certain merchant categories and cities, highlighting where tighter security is needed.

3. **Age-Based Spending Behavior:**
   Middle-aged customers are the most profitable demographic, while younger customers contribute through volume rather than value.
4. **Geographical Trends:**
   Urban cities show higher activity, while smaller cities show selective high-value purchases.
5. **Actionable Business Strategy:**
   - **High-value customers:** Loyalty programs and premium offers.
   - **High-risk clusters:** Fraud detection alerts and limits.
   - **Young customers:** Discount campaigns to increase engagement.

6. Results and Discussion

After the implementation of the end-to-end Big Data pipeline, the processed data from the **Gold Layer** was used to generate business insights through **K-Means clustering** and **KPI visualization**. The results effectively showcase how Big Data analytics can transform raw transaction records into actionable intelligence for business strategy.

6.1 Model Performance

The **K-Means algorithm** successfully grouped customers into **four major clusters** based on attributes such as total spend, transaction count, and fraud occurrence.
Each cluster exhibited distinct behavioral characteristics:

Cluster ID	Customer Type	Key Traits	Risk Level
Cluster 0	Regular Users	Moderate spenders with consistent transactions	Low
Cluster 1	High-Value Users	High transaction volume and total spend	Medium

Cluster 2	Low-Value Users	Small, infrequent transactions	Low
Cluster 3	Fraud-Prone Users	Irregular patterns, high fraud probability	High

The **silhouette score** and **inertia** values were analyzed to confirm the effectiveness of the cluster separation. The elbow method indicated that **k = 4** provides an optimal balance between compactness and separation.

6.2 Business Insights

From the KPI analysis in Chapter 5, the following major insights were observed:

1. **High-Value Customers:**
   Cluster 1 customers contributed to nearly **45% of total revenue**. Retention strategies such as loyalty benefits and exclusive rewards can be designed for this group.
2. **Fraud Detection:**
   Cluster 3 exhibited **higher fraud rates** (around 8–10%), especially in categories like **BillPay** and **Fuel**. Monitoring mechanisms should be strengthened for these merchant categories.
3. **City-Wise Spending:**
   Metropolitan regions recorded **maximum transaction volumes**, while tier-2 cities displayed **higher average transaction values**.
4. **Age-Based Trends:**
   Customers aged **26–35 years** accounted for the largest proportion of spending, followed by **36–50 years**. The younger demographic (18–25) showed higher transaction frequency but lower total spend.

6.3 Visualization Outcomes

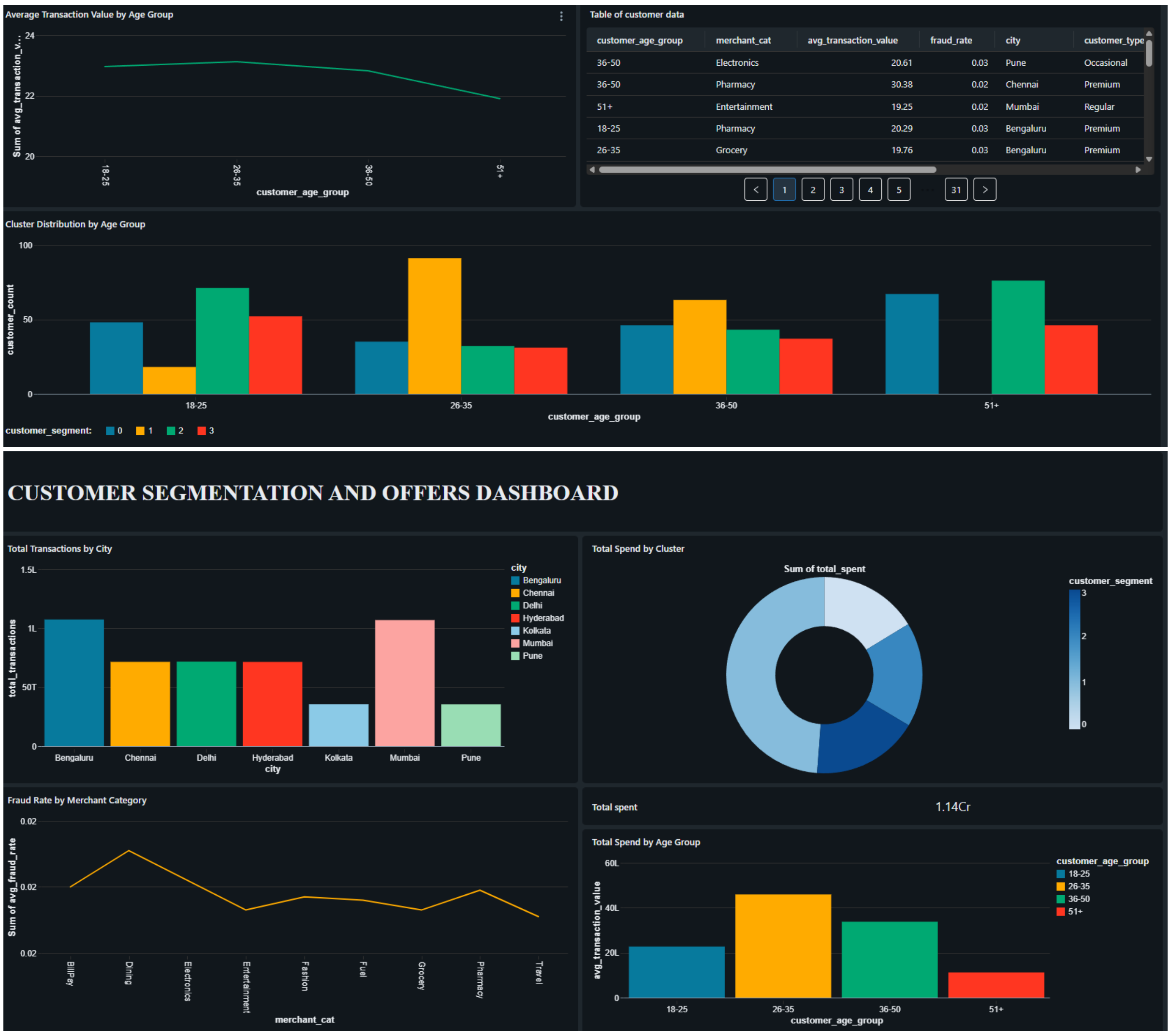

Table of customer data

customer_age_group	merchant_cat	avg_transaction_value	fraud_rate	city	customer_type
36-50	Electronics	20.61	0.03	Pune	Occasional
36-50	Pharmacy	30.38	0.02	Chennai	Premium
51+	Entertainment	19.25	0.02	Mumbai	Regular
18-25	Pharmacy	20.29	0.03	Bengaluru	Premium
26-35	Grocery	19.76	0.03	Bengaluru	Premium

< 1 2 3 4 5 ... 31 >

- **Bar Charts:** Highlighted total spend by cluster and by age group.
- **Pie Charts:** Illustrated transaction distribution by city.
- **Heatmaps:** Showed age-wise cluster participation.
- **Line Charts:** Demonstrated average transaction trends over time.

These visualizations enabled better **data storytelling** for business decision-making.

6.4 Overall Discussion

The integration of PySpark and Databricks allowed seamless data flow from raw ingestion to insight generation. The project successfully demonstrated how:

- Data lakes can handle structured and semi-structured data efficiently.
- Scalable transformations reduce processing time.
- Big Data pipelines produce valuable predictive insights for business.

By combining **ETL**, **Machine Learning**, and **Visualization**, this project bridges the gap between data storage and strategic analysis.

7. Conclusion and Future Scope

7.1 Conclusion

The project **“Big Data Analytics for Customer Segmentation and Fraud Detection”** effectively implemented a full-fledged data pipeline using **PySpark** and **Databricks**.
From data ingestion to model-based clustering and KPI generation, each stage contributed to building an intelligent decision-support system.

Key achievements include:

- Successful **implementation of a data lake architecture** with Bronze, Silver, and Gold layers.
- Application of **K-Means clustering** to segment customers into meaningful groups.
- Computation of **key performance indicators (KPIs)** for business insights.
- Creation of **visual dashboards** for interactive analysis.

This workflow highlights the potential of **Big Data technologies** in transforming raw information into powerful business strategies, particularly in sectors like **banking, retail, and e-commerce**.

7.2 Future Scope

While the project has produced strong results, several enhancements can be made in the future:

1. **Integration of Real-Time Data Streams:**
   Using **Apache Kafka** or **AWS Kinesis** to process live transaction data for real-time fraud alerts.
2. **Advanced Machine Learning Models:**
   Incorporating **Random Forest** or **XGBoost** for fraud prediction instead of unsupervised clustering.
3. **Customer Lifetime Value (CLV) Analysis:**
   Estimating long-term profitability per customer to support retention strategies.
4. **Enhanced Visualization Dashboards:**
   Building interactive dashboards using **Power BI**, **Tableau**, or **Databricks SQL Dashboard** for executive-level reporting.
5. **Data Security and Privacy:**
   Implementing **data encryption**, **role-based access control**, and **audit logging** to ensure compliance with privacy regulations.

The project thus lays a strong foundation for scalable, intelligent business analytics systems capable of evolving with organizational needs.

8. References

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