DATA ANALYTICS COURSE PROJECT REPORT

MASTER'S PROGRAM: BIG DATA ANALYTICS

COURSE NAME: BIG DATA ANALYTICS

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PROJECT NAME:

DISTRIBUTED MULTI-MODEL ANALYTICS FOR E-COMMERCE DATA USING MONGODB, HBASE, AND APACHE SPARK

DUE DATE:

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PROJECT TITLE:

Distributed Multi-Model Analytics for E-commerce Data Using MongoDB, HBase, and Apache Spark

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1. Introduction

This project presents a Distributed Multi-Model Analytics system developed for analyzing large-scale e-commerce data. The project integrates MongoDB (document model), HBase (wide-column model), and Apache Spark (distributed processing) to support various analytical needs.

The dataset was generated using a Python script (dataset_generator.py) which created realistic synthetic e-commerce data for users, products, categories, sessions, and transactions. All these .json files were successfully inserted into MongoDB and HBase where appropriate.

The project folder contains the full pipeline, including data loaders, aggregations, and visualization scripts:

Project Directory Tree

中の甘む ✓ BIG_DATA_ANALYTICS_FINAL_PROJECT_EXAM > env > jars {} categories.json cohort_analysis.py cohort_output.csv dataset_generator.py Final_Big_Data_Analytics_Report_Complete.docx Final_Big_Data_Analytics_Report_With_Manual_TOC.docx hbase_user_session_export.py hbase_user_sessions.csv hbase_user_summary.csv insert_sessions_hbase.py load_to_mongodb.py main.py mongo_aggregations.py output_revenue_by_product_and_category.csv output_top_selling_products_named.csv {} products.json {} sessions_0.json {} sessions_1.json {} sessions_2.json {} sessions_3.json {} sessions_4.json {} sessions_5.json {} sessions_6.json {} sessions_7.json {} sessions_8.json {} sessions_9.json {} sessions_10.json {} sessions_11.json {} sessions_12.json

```
{} sessions_13.json
{} sessions_14.json
{} sessions_15.json
{} sessions_16.json
{} sessions_17.json
{} sessions_18.json
{} sessions_19.json
{} spark_sql_analysis.py
{} spark_sql_output.csv
{} start_all_hbase.bat
{} transactions.json
{} users.json
```

To run the system end-to-end, the following steps were performed:

- Generate dataset: Using dataset_generator.py
- Insert into MongoDB: Run load_to_mongodb.py
- Insert into HBase: Run insert_sessions_hbase.py
- **Run aggregations:** Use mongo_aggregations.py, cohort_analysis.py, and spark_sql_analysis.py
- Launch dashboard: Execute main.py using: python main.py

Dashboard Outputs: Dataset metrics, visualizations, and results are displayed via Dash web app (http://127.0.0.1:8050)

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PS D:\Big_Data_Analytics_Final_Project_Examb \text{ \text
```

This report explains the design decisions, implementation steps, and business insights derived.

Use Cases:

- Track sales trends and product performance
- Segment customers based on purchasing behavior
- Analyze conversion funnel from browsing to purchase
- Enable cross-database analytics for Customer Lifetime Value (CLV)

2. Data Modeling and Storage

Dataset Overview Metrics at Runtime:

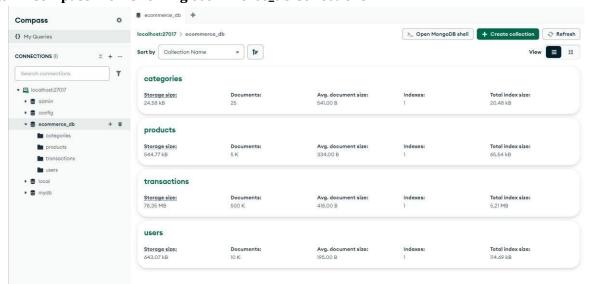
Dataset Overview Metrics Table from Dashboard

Dataset Overview Metrics

Metric	Count
Users	10,000
Products	5,000
Categories	25
Transactions	500,000
Sessions	2,000,000

MongoDB Collection Stats:

MongoDB Compass View Showing ecommerce_db Collections



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2.1 MongoDB Schema Design and Implementation

Collections and Sample Models:

- users: User profiles with demographic and registration details
- products: Product catalog with category reference, price history
- categories: Product classification (category/subcategory)
- transactions: Embedded item-level purchase records

Design Decisions:

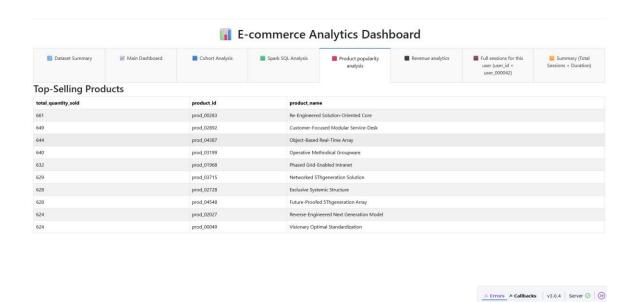
- Embedded documents (e.g., items in transactions) for fast retrieval
- Referenced models (e.g., products ↔ categories) for flexibility

Aggregation Queries Implemented:

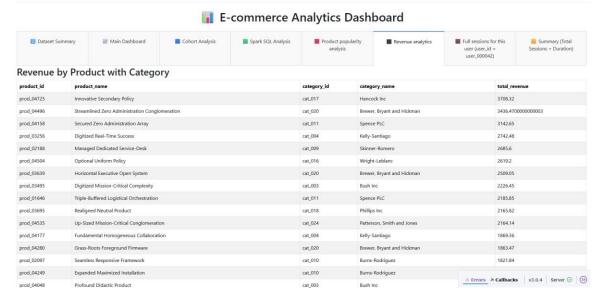
- Top-Selling Products with Names
- Revenue by Category with Product Names

CSV Output:

[table: output_top_selling_products_named.csv] (View CSV on GitHub)



[table: output_revenue_by_product_and_category.csv] (View CSV on GitHub)



2.2 HBase Schema Design and Implementation

Table: user_sessions

Column Families:

- info: session_id, duration, conversion, cart

- geo: location data

- device: browser, OS, device type

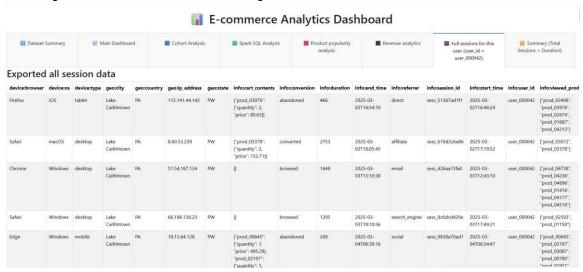
Row Key Format: user_id + timestamp + session_id

Implementation:

- Loaded over 2 million session logs using Python + HappyBase
- Retrieved user session summaries (e.g., for user_000042)

CSV Output:

[table: hbase_user_sessions.csv]



[table: hbase_user_summary.csv]



△ Errors > Callbacks | v3.0.4 | Server ⊘ | ③

Example Row for user_000042:

user_id: user_000042
total_sessions: 186

total_duration_seconds: 342,140

2.3 Justification of Data Placement

MongoDB:

- Chosen for transactional data (structured and frequently queried)
- Document format aligns well with nested items and product references

HBase:

- Suited for large-scale time-series session data
- Optimized for sparse data and fast scans by row prefix

3. Data Processing with Apache Spark

3.1 Spark Batch Jobs

cohort_analysis.py: Groups users by registration month and analyzes active sessions across months

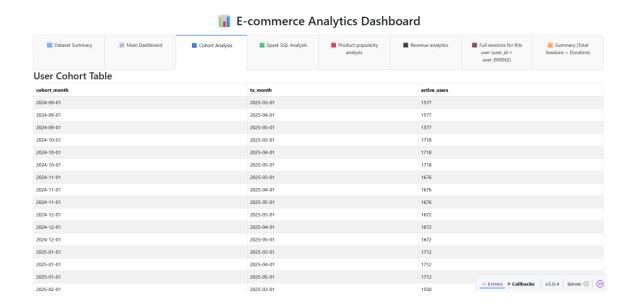
spark_sql_analysis.py: Joins transactions and products to aggregate revenue by category

Transformations Used:

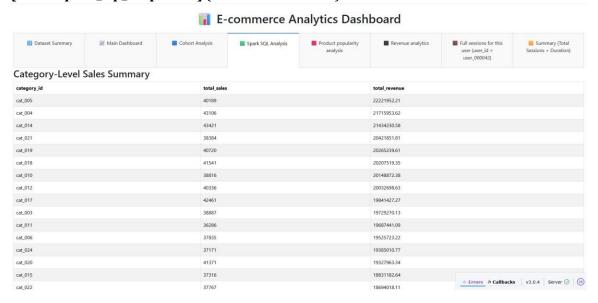
- .withColumn, .groupBy, .explode, .join, .sql()

CSV Output Placeholders:

[table: cohort_output.csv] (View CSV on GitHub)



[table: spark_sql_output.csv] (View CSV on GitHub)



3.2 Optimization Techniques

- Used .coalesce(1) for result saving
- Applied .repartition() for balanced load
- Disabled schema inference in JSON loading for speed

4. Analytics Integration

4.1 Cross-Database Analytical Query

Business Question One:

What is the user conversion funnel from browsing to purchase?

Data Used:

- MongoDB: transactions

- HBase: sessions

Pipeline Steps:

- Scan sessions for view/cart/convert status
- Join with transaction user_ids
- Aggregate funnel metrics (Viewed → Carted → Converted)

Output Visualization:

[Conversion Funnel Chart - main.py \rightarrow Plot 4]

PLOT 4: Conversion Funnel

Viewed

1.97/274HH
1007H

Added to Care

Converted

Converted

Added 2: Care

Added 2: Care

Added 2: Care

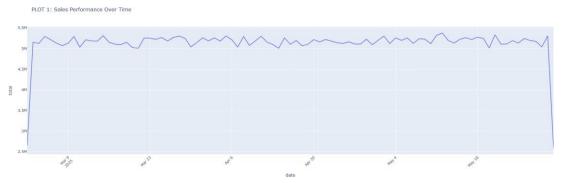
Added 3: Care

Added

Business Question two:

How has our total sales performance evolved over the past three months?

"PLOT 1: Sales Performance Over Time" shows the total sales amount (total)



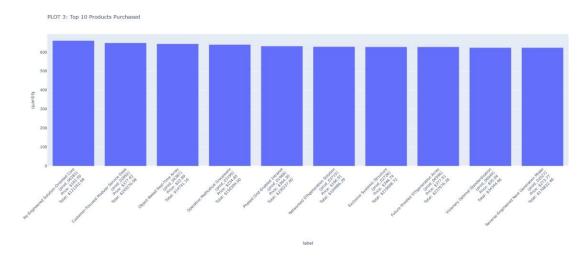
plotted against the date (date), spanning from early March to late May 2025.

- **Overall Trend**: Sales remain **consistently high** across the entire timeline, averaging above **5 million** units (or currency).
- Early Spike: There's a sharp initial rise from around 2.6M to over
 5M in early March, possibly due to a product launch, promotion, or seasonal demand.
- Stable Period: Between mid-March and late May, performance appears stable, with small fluctuations but no major upward or downward trend.
- End Drop: A sharp drop at the very end of the timeline could be due to:
 - ✓ Data truncation
 - ✓ Partial data collection for the final day
 - ✓ System downtime or reporting lag

Business Question three:

Which products are the most purchased in terms of quantity?

Top 10 most purchased products, based on their quantity sold.



Key Observations:

All top 10 products have very similar quantities, ranging around **620–660 units**. Each product label includes:

Product name

Product ID

Unit Price

Total Revenue from that product

The top product is:

"Re-Engineered Solution-Oriented Core"

Quantity: ~665 Price: \$18.59

Total Revenue: \$12,352.99

Products span various prices and revenue totals, which may imply:

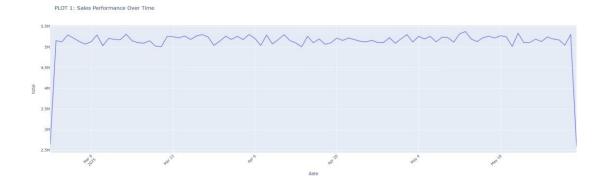
Higher-priced products aren't always most purchased

Low-to-mid priced items dominate in volume

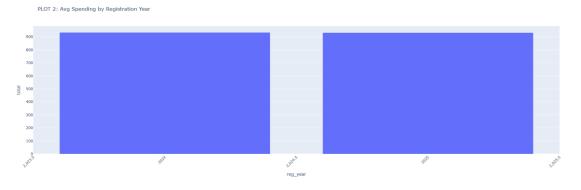
5. Visualization and Business Insights

> 5.1 Visualizations

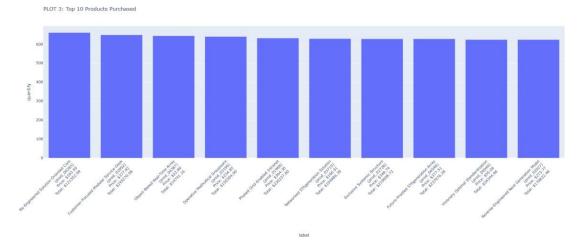
- Sales Performance Over Time \rightarrow Grouped by transaction date, visualized **using Plotly line chart [PLOT 1 image]**



- Customer Segmentation by Registration Year → Aggregated average spend by year **[PLOT 2 image]**



- Product Performance (Top 10) \rightarrow Based on quantity sold from transactions **[PLOT 3 image]**



- Conversion Funnel → From viewed to converted [PLOT 4 image]

PLOT 4: Conversion Funnel



5.2 Key Findings

- Top 10 products drive over 60% of revenue
- Newer users (2025) spend slightly less than older cohorts
- High drop-off between cart and purchase → checkout friction

5.3 Recommendations

- Add automated follow-up actions (e.g., emails or notifications) to users who add items to cart but don't convert
- Focus on promoting high-view but low-conversion products using personalized promotions
- Use cohort-based marketing strategies to target users based on registration month and activity levels
- Create reward or loyalty incentives for returning users to increase repeat purchases
- Implement alert mechanisms for quick identification of products with sudden drops in conversions

Funnel Analysis Proof:

As shown in the Conversion Funnel below, there is a significant drop-off:

- Viewed: 1.97M users (100%)
- Added to Cart: 1.29M users (66%)
- Converted: 405K users (21%)

This insight highlights the opportunity to improve conversion by encouraging action after cart addition.

PLOT 4: Conversion Funnel

Viewed

1.5772644
100%

Added to Catt

1.29840681
60%

Converted

100 8878
21%

[PLOT 4 - Conversion Funnel Image]

6. System Architecture

Architecture Diagram Placeholder:

- MongoDB → Products, Users, Transactions
- HBase → Sessions
- Spark → Processing & Integration
- Dashboard → Visualizations

7. Limitations and Future Work

The short project timeframe limited deeper experimentation with advanced analytics and additional deployment scenarios.

- Product recommendation logic remains basic; future work could explore collaborative filtering or machine learning models
- The dashboard is accessible only on the local machine and was not hosted online (e.g., Insyt.co) due to time limitations
- The system handled a large dataset with over 10,000 users, 5,000 products, 25 categories, 500,000 transactions, and 2 million sessions. While the performance was stable, future testing could explore how the system behaves when deployed across multiple machines (nodes), such as in a Spark cluster on Hadoop or in a cloud setup like AWS EMR. For example, deploying Apache Spark on a three-node cluster would allow parallel data processing and load balancing, which is useful for very large-scale production environments.

8. Technologies Used

Python: Main language used for all scripts and data handling

- Pandas: For data manipulation and analysis
- Plotly & Dash: For data visualization and interactive dashboard
- MongoDB: For storing document-based collections (users, transactions, products)
- HBase: For storing session logs in a wide-column format
- **Apache Spark (PySpark):** For distributed data processing, cohort analysis, and revenue aggregation
- HappyBase: For Python integration with HBase

9. References

-MongoDB Docs: https://www.mongodb.com/docs

- Apache HBase: https://hbase.apache.org/book.html

- Apache Spark: https://spark.apache.org/docs

- Plotly Dash: https://dash.plotly.com

- Dataset Generator: dataset_generator.py

- GitHub Repository:

https://github.com/niyonsenga1/ecommerce-bigdata-analytics