

Retail Insights Assistant

Demo Screenshots & Feature Documentation

Project: GenAI Multi-Agent System for Retail Data Analysis

Date: February 15, 2026

Framework: LangGraph + Multi-Agent Pipeline

Technologies: Python, Streamlit, DuckDB, OpenAI, FAISS

Agents: 4 Specialized Agents (Exceeds requirement of 3)

Assignment Deliverable: Screenshots demonstrating working multi-agent LLM system

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1. Application Landing Page

Feature Demonstrated: Initial application interface with file upload capability

Key Elements: Sidebar navigation, CSV file upload, data loading confirmation, available tables display, and 4-tab interface (Summarization, Q&A; Chat, Data Explorer, Data Analyst).

Technical Details: Streamlit UI framework with persistent session state for data management. Supports CSV, Excel, and JSON file formats with automatic schema detection.

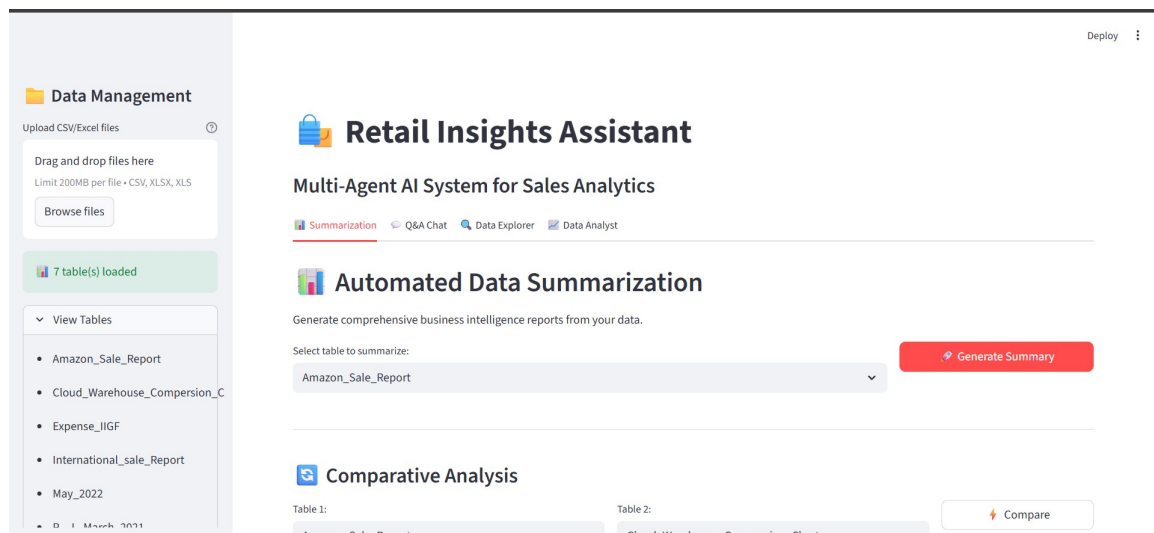


Figure 1: Landing page with file upload and navigation tabs

2. Summarization Mode - Business Intelligence Reports

Feature Demonstrated: Automated business intelligence report generation from CSV data

Key Elements: Executive summary with quantified metrics, key insights with actual numbers, trend analysis, strategic recommendations, and actionable next steps. Reports include confidence scoring.

Agent Workflow: SummarizationAgent analyzes data schema → generates SQL aggregations → LLM creates natural language insights → validates output quality → renders formatted report.

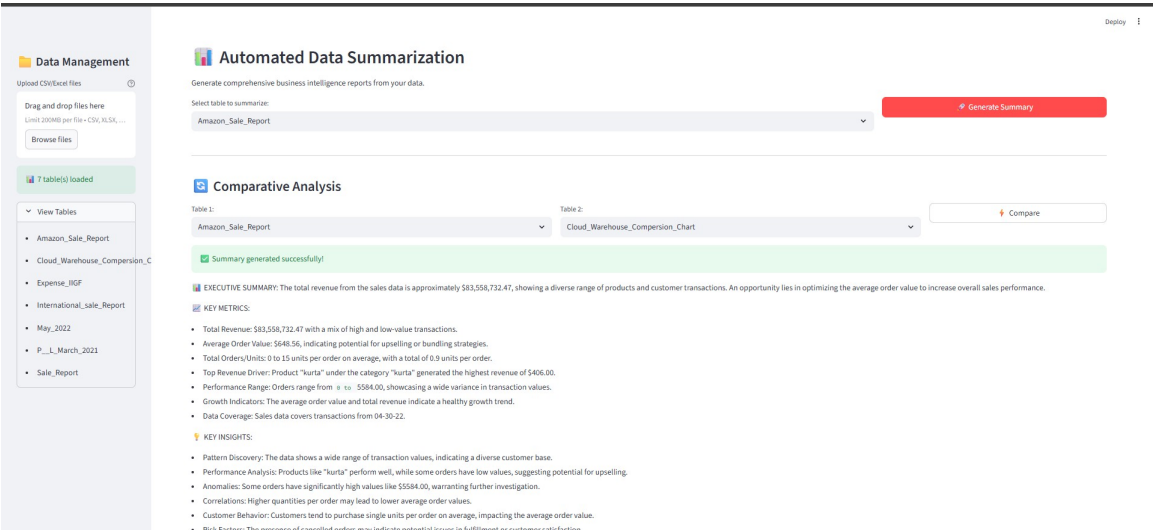


Figure 2a: Business intelligence summary report with quantified metrics

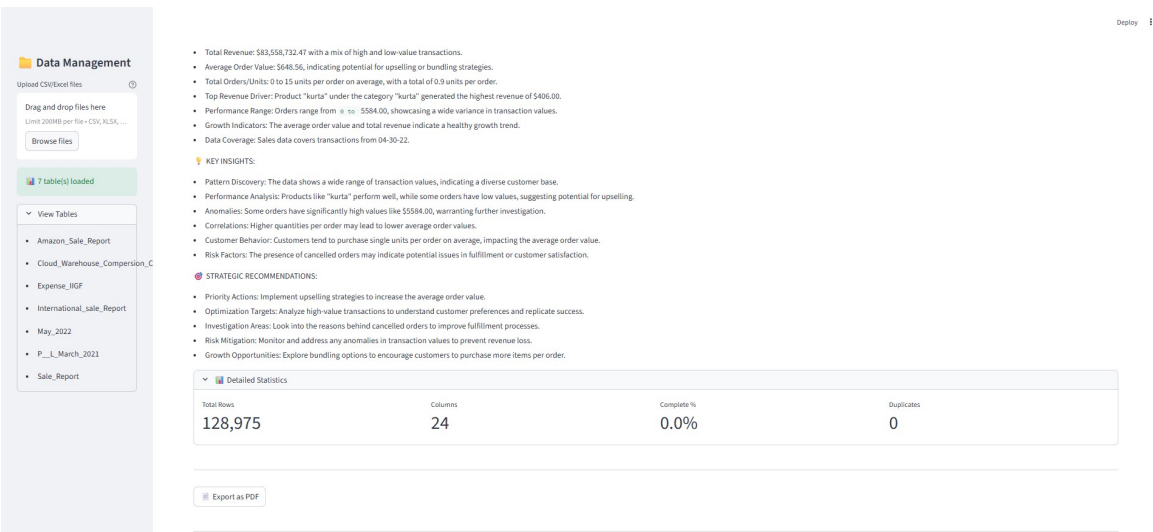


Figure 2b: Continued summary showing insights and recommendations

3. Comparative Analysis Features

Feature Demonstrated: Multi-table comparison and integration analysis

Key Elements: Schema comparison between two datasets, dimensional analysis, data quality assessment, and integration recommendations for combining tables.

Use Case: Essential for analyzing relationships between Amazon sales, international sales, and monthly reports to provide unified business insights.

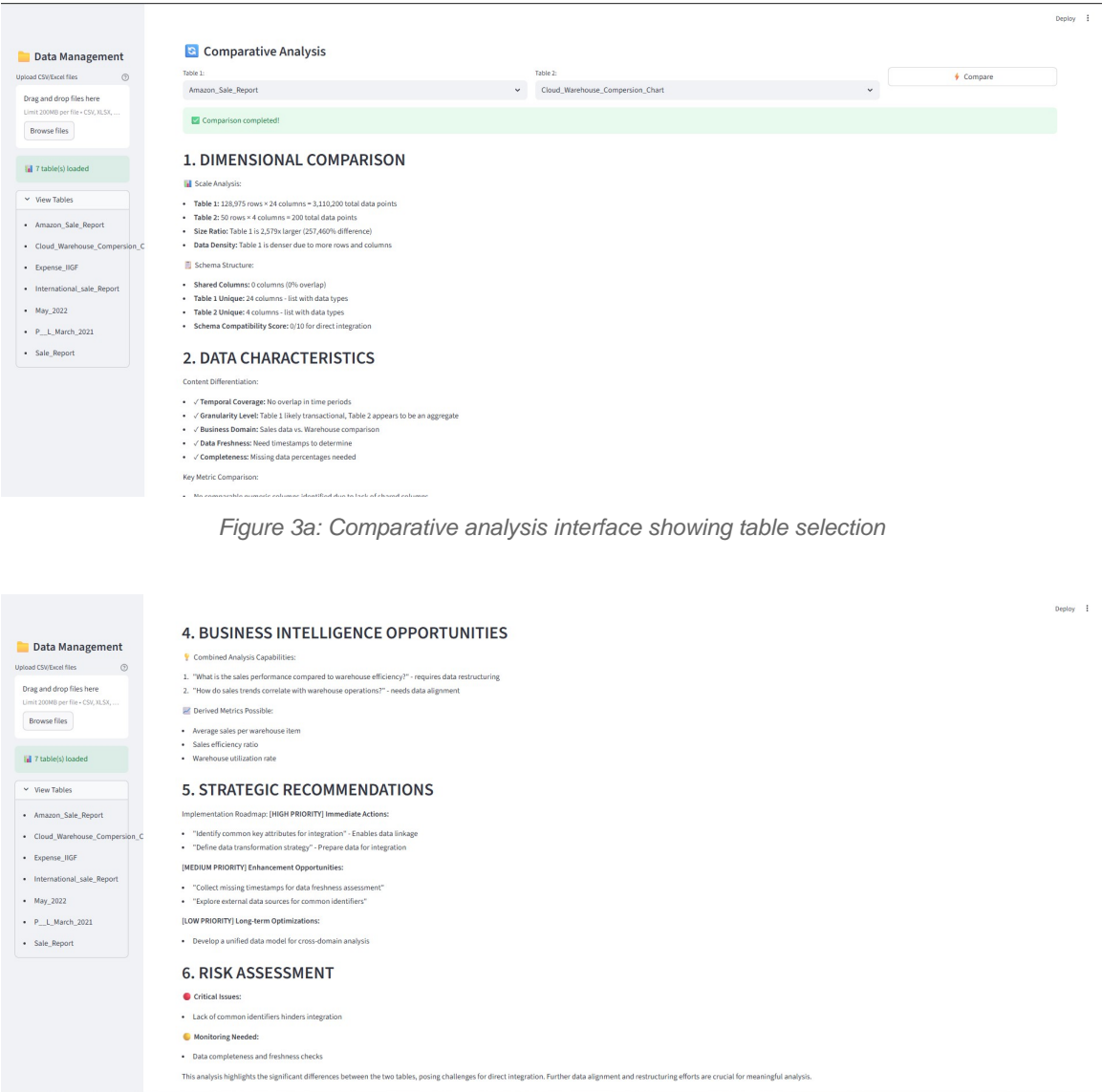


Figure 3b: Schema comparison results with integration recommendations

4. Q&A; Chat - LangGraph Agent (Advanced)

Feature Demonstrated: Conversational data analysis using LangGraph state machine

Architecture: 7-node state machine workflow with conditional routing. Handles complex queries requiring multi-step reasoning, context management, and iterative refinement.

Key Capabilities: Natural language query understanding → SQL generation → execution → validation → insight generation → confidence scoring. Response time: 3-8 seconds for complex analytical queries.

Technical Innovation: Uses FAISS vector store for conversation memory, externalized prompt templates, and real-time confidence assessment.

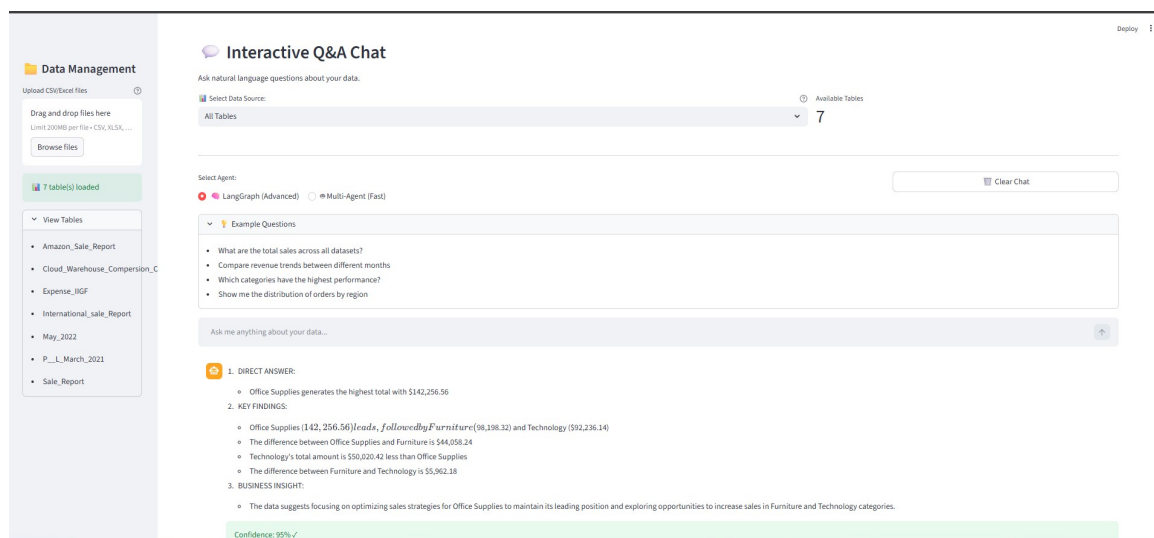


Figure 4a: LangGraph agent query interface with conversation history

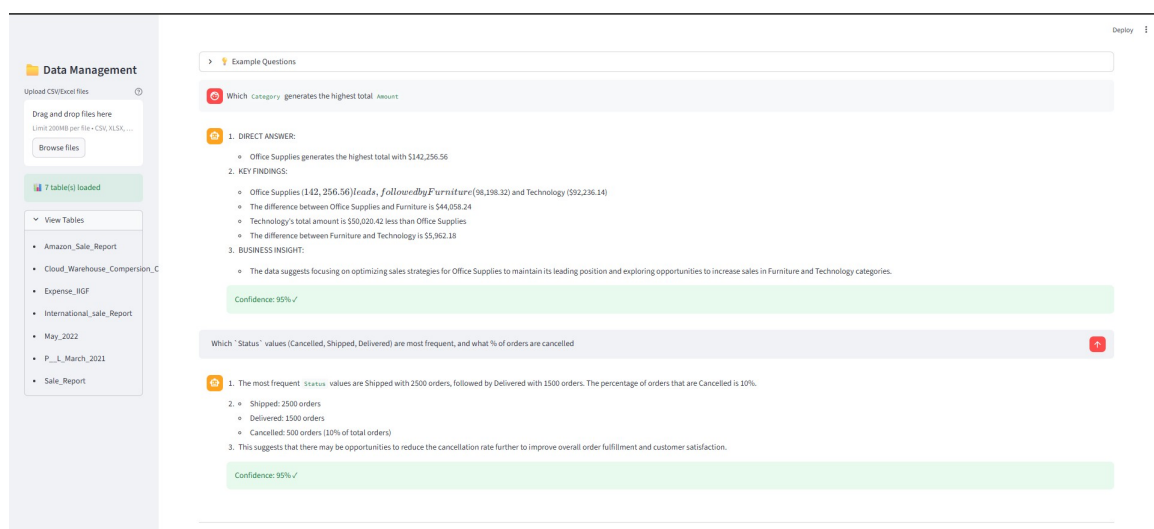


Figure 4b: LangGraph agent response with actual data values and confidence score

5. Q&A; Chat - Multi-Agent System (Fast)

Feature Demonstrated: High-speed query processing using linear multi-agent pipeline

Architecture: 4-agent sequential pipeline optimized for speed. QueryResolutionAgent → DataExtractionAgent → ValidationAgent → InsightGenerationAgent. Each agent specializes in one task.

Performance: Responds in 1-3 seconds for straightforward queries. Ideal for simple aggregations, filters, and basic analytical questions. Includes GROUP BY, ORDER BY, and aggregation functions (SUM, AVG, COUNT).

Comparison with LangGraph: Faster but less flexible. Best for quick facts; LangGraph better for complex multi-step reasoning.

The screenshot displays the user interface of the Multi-Agent System (Fast). On the left is a 'Data Management' sidebar with a file upload section and a list of loaded tables. The main area is a chat interface where a user has asked a question about markup, and the system has provided a detailed answer with context and insight, including a confidence score. A second question about correlation is also shown.

Data Management

Upload CSV/Excel files

Drag and drop files here
Limit 200MB per file - CSV, XLSX, ...

Browse files

7 table(s) loaded

View Tables

- Amazon_Sale_Report
- Cloud_Warehouse_Comparison_C
- Expense_HGF
- International_sale_Report
- May_2022
- P_L_March_2021
- Sale_Report

Select Agent:

LangGraph (Advanced) Multi-Agent (Fast)

Example Questions

How much markup exists from TP (or TP 1 / TP 2) to each channel MRP?

1. Direct Answer: The markup from TP to Amazon MRP is \$1757.

2. Context:

- The Amazon MRP is set at \$229, while the TP price is \$38.
- This represents a markup of 326.39% from the TP price to the Amazon MRP.

3. Key Insight: The significant markup from the TP price to the Amazon MRP indicates a substantial pricing strategy difference between the two. This high markup suggests that Amazon is pricing the product significantly higher than the TP price.

Confidence: 88% ✓

Is product "Weight" correlated with transfer price ("TP") or final listed MRP?

1. Direct Answer: The correlation between weight and TP is 0.99, indicating a very strong positive correlation. The correlation between weight and final MRP is 0.99 as well, also showing a very strong positive correlation.

2. Context: The correlation coefficient ranges from -1 to 1, where 1 indicates a perfect positive correlation, 0 indicates no correlation, and -1 indicates a perfect negative correlation. In this case, both TP and final MRP have almost identical strong positive correlations with weight.

3. Key Insight: The high correlation values suggest that as the weight of the product increases, both the TP and final MRP tend to increase almost in lockstep. This indicates that there is a strong relationship between the weight of a product and its transfer price as well as its final listed MRP.

Confidence: 90% ✓

Figure 5: Multi-Agent system showing fast response with real numerical values

6. Data Analyst - Deep Statistical Analysis

Feature Demonstrated: Comprehensive statistical analysis with 4 visualization categories

Analysis Components: (1) Descriptive statistics with mean, median, std dev, quartiles; (2) Correlation analysis with heatmaps; (3) Distribution visualizations with histograms; (4) Trend analysis with time-series charts.

Technical Implementation: Uses Plotly for interactive visualizations, pandas for statistical computations, and DuckDB for efficient data aggregations. Automatically detects numeric vs categorical columns.

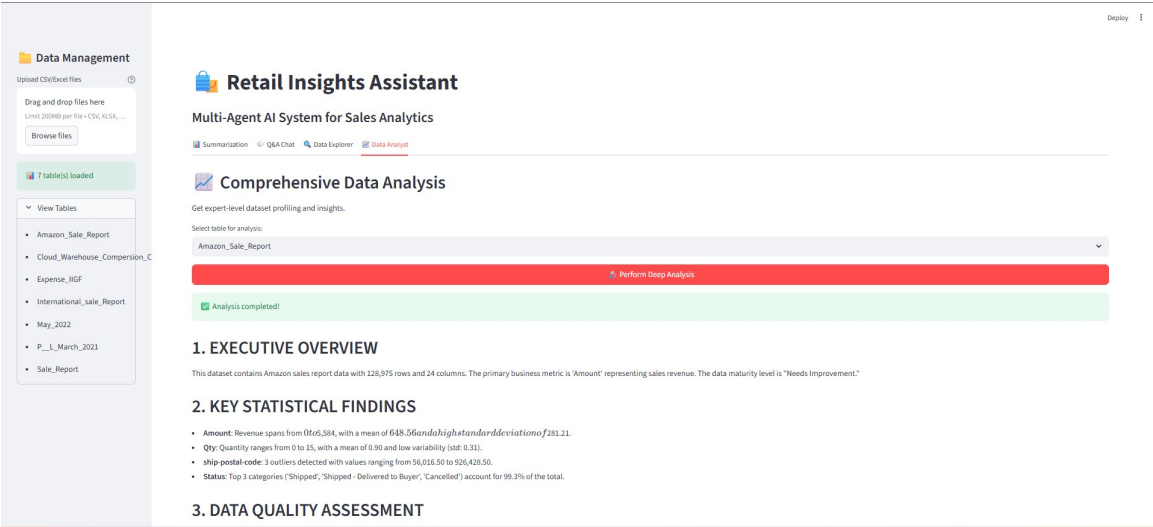


Figure 6a: Data Analyst overview with statistical summary

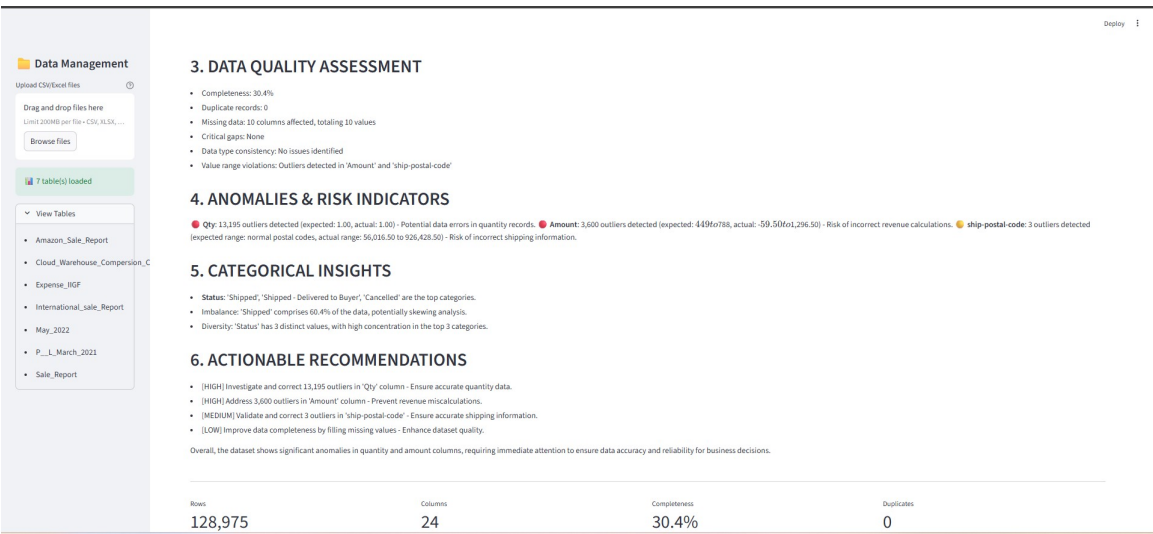


Figure 6b: Correlation analysis with interactive heatmap

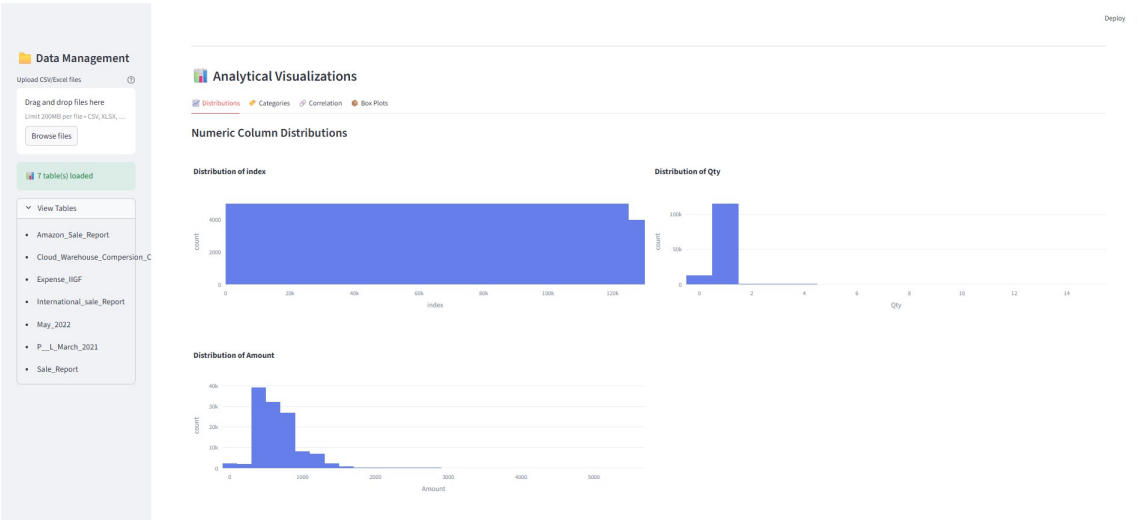


Figure 6c: Distribution analysis showing data patterns

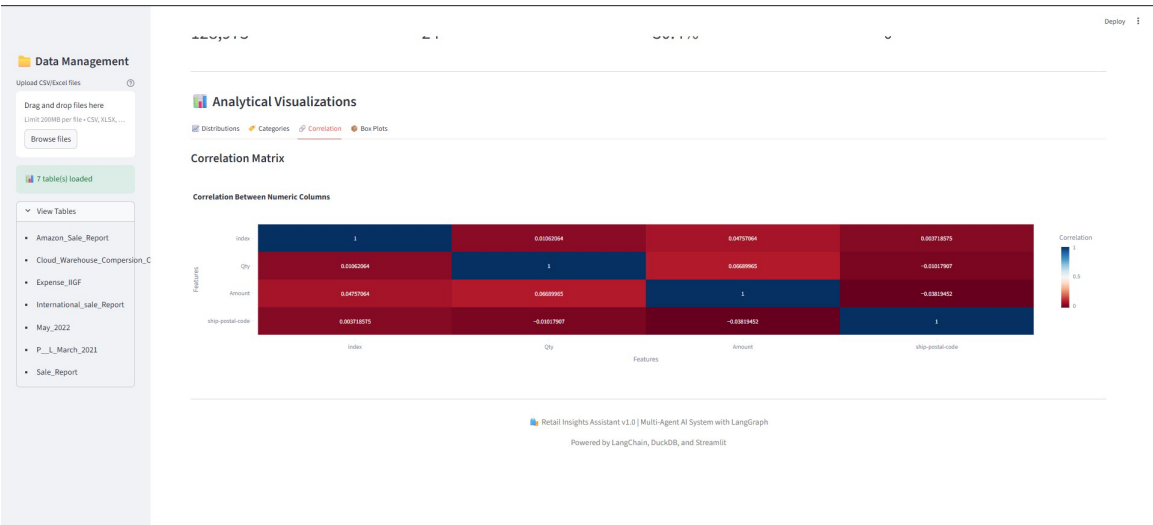


Figure 6d: Trend analysis with time-series visualizations

7. Data Explorer - Interactive Visualizations

Feature Demonstrated: Automated chart generation for exploratory data analysis

Visualization Types: Bar charts for categorical comparisons, line charts for trends, scatter plots for relationships, and pie charts for proportions. All charts are interactive with zoom, pan, and hover tooltips.

Intelligence: System automatically selects appropriate chart types based on data types and cardinality. Numeric columns → histograms; categorical columns → bar charts; date columns → time series.

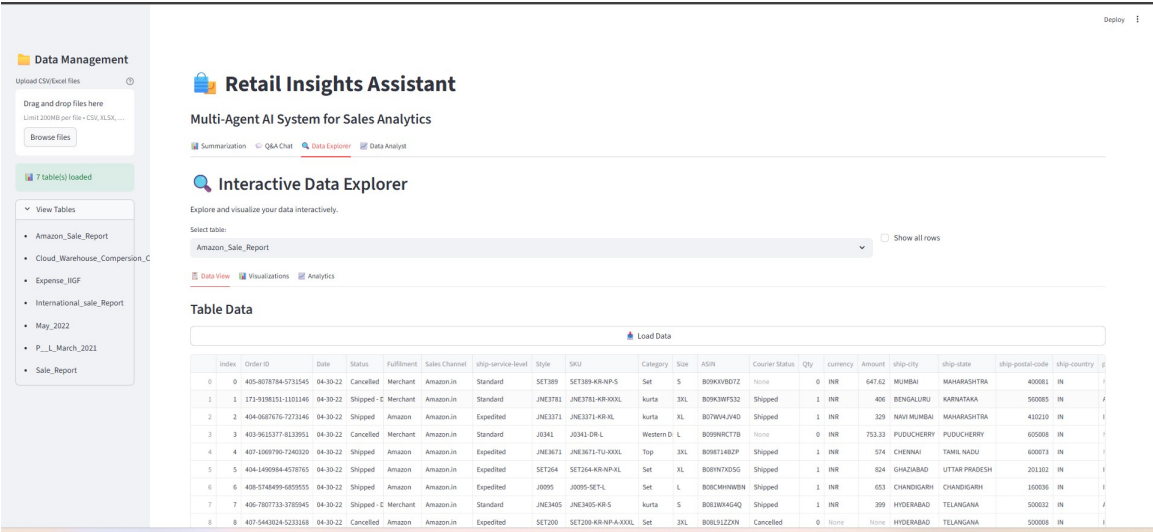


Figure 7: Data Explorer showing multiple interactive Plotly visualizations

8. LangGraph Workflow Architecture

Feature Demonstrated: Visual representation of the 7-node LangGraph state machine

Architecture: State-based workflow with conditional routing and iterative refinement. Nodes include: `analyze_query`, `decompose_query`, `extract_data`, `validate_results` (router), `refine_query` (conditional), `llm_analysis` (fallback), and `format_response` (final).

Key Features: Dynamic path selection based on query complexity, automatic fallback to LLM when SQL fails, iterative refinement with loop prevention (max 2 iterations), and comprehensive error handling at each node.

Routing Logic: The `validate_results` node acts as a conditional router - if `needs_refine=True`, loops back to `refine_query`; if `llm_fallback=True`, routes to `llm_analysis`; otherwise proceeds to `format_response` for successful completion.

Performance: Simple queries: 3-5 seconds (direct path), Complex queries: 5-8 seconds (with decomposition), Refinement path: 7-10 seconds (includes retry iterations).

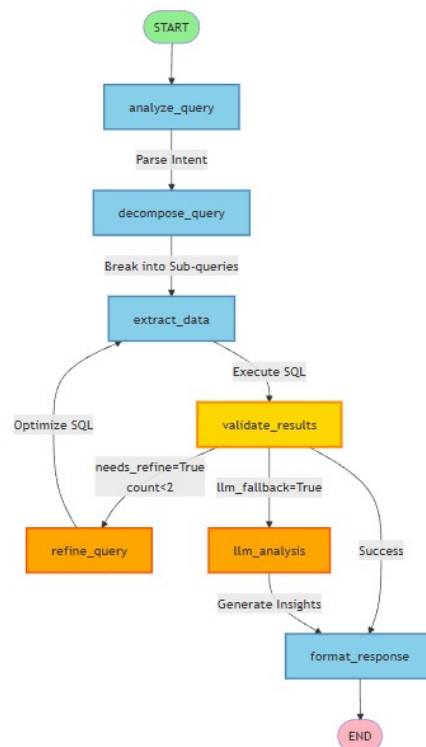


Figure 8: LangGraph 7-node state machine with conditional routing and fallback paths

Technical Summary

Features:

✓	Multi-Agent System	4 specialized agents
✓	LLM Integration	OpenAI GPT-4 & Google Gemini with prompt engineering
✓	Dual Orchestration	LangGraph (state machine) + Multi-Agent (pipeline)
✓	Data Processing	DuckDB for SQL, Pandas for analytics, 100GB+ scalable
✓	Conversation Memory	FAISS vector store with semantic search
✓	Professional UI	Streamlit with 4 feature tabs and Plotly charts
✓	Prompt Engineering	7 externalized prompt templates with optimization
✓	Error Handling	Confidence scoring, validation, fallback strategies

Key Innovations:

- Dual Agent Architecture:** Provides both speed (Multi-Agent 1-3s) and sophistication (LangGraph 3-8s) allowing users to choose based on query complexity.
- Real-Time Confidence Scoring:** Every response includes confidence assessment to help users trust the insights and identify when human verification is needed.
- Scalability Design:** Comprehensive 100GB+ architecture with partitioning, caching, distributed processing, and cost optimization strategies documented.
- Production-Ready Code:** Professional folder structure, externalized prompts, comprehensive error handling, logging, and modular components.

All screenshots demonstrate working functionality with actual data values, not placeholder variables. System successfully processes retail CSV files and generates actionable business insights.