## Retrieval to Reasoning: RAG & AI Agents on Azure Databricks



Hemamalini Nithyanandam Ashwini Mahendran



#### AGENDA

#### Retrieval to Reasoning: RAG & Al Agents on Azure Databricks

- 01 | Evolution From Retrieval to Reasoning
- 02 | Context Aware RAG on Azure databricks
- 03 | Agentic RAG
- 04 | Al Agents & RAG in Azure databricks
- 05 | RAG datapipeline
- 06 | Agentic RAG Usecases Demo
- 07 | Best Practices & Future of RAG & Al Agents

## Who Am I....

### Professional

- Software Designer in HP
- 12+ years IT experience
- AWS Solutions Architect
- Data Engineer&
- AI Enthusiast



#### Personal

- Punnagai Foundation
- Certified Yoga Trainer
- Blogs

https://www.linkedin.com/in/hemamalini-nithyanandam/



## Who Am I ....

### Professional

- Senior Software Engineer at ATMECSAI
- Al researcher & developer
- Embedded and Cloud based full stack AI development



#### Personal

- Badminton Player
- Mandala Artist

https://www.linkedin.com/in/ashwinimahendiran/



Evolution – From Retrieval to Reasoning

## Evolution – From Retrieval to Reasoning

#### What are LLMs?

- Large Language Models (e.g., GPT-4, BERT) are deep learning models trained on vast amounts of text data.
- They generate human-like text based on input queries or prompts.

#### Key Characteristics of LLMs:

- Powerful in understanding and generating text.
- Context-dependent: rely on pre-trained knowledge, limited to training data.

#### Limitations:

- Static, unable to access real-time or updated information.
- Responses are limited to what the model has learned during training.

#### What is Retrieval-Augmented Generation (RAG)

#### **RAG: A Hybrid AI Model**

Combines the power of LLMs with real-time information retrieval.

#### **Two Components:**

- Retrieval: Dynamically fetches relevant data from external sources (e.g., databases, APIs).
- Generation: LLM refines and generates context-aware responses using the retrieved data.

## Why RAG Matters?

#### **Limitations of Traditional LLMs**

- Static and limited knowledge
- Prone to hallucinations (inaccurate responses)
- Lacks real-time context awareness

#### **How RAG Enhances LLMs**

- Integrates external and real-time data
- Reduces hallucinations by grounding responses in facts
- Delivers accurate, up-to-date insights
- Improves relevance and precision by incorporating contextspecific knowledge

## Enhancing LLMs with Context-Aware Data

#### **Static LLMs vs. Dynamic Knowledge**

• LLMs alone are limited by the data they were trained on, lacking the ability to adapt to real-world, real-time situations.

#### **Benefits of RAG:**

- **Accuracy**: By retrieving relevant information from up-to-date sources, RAG ensures responses are grounded in reality.
- **Context-Awareness**: Improves understanding of context and generates more precise and relevant responses.
- Adaptability: Handles a wide range of topics with ease by accessing external knowledge on demand.

#### Context-Aware RAG on Azure Databricks

#### **Key Components:**

- **Retriever:** Searches knowledge bases (Vector DBs, SQL, Delta Lake)
- Generator (LLM): Uses retrieved data for contextual responses
- Feedback Loop: Ensures accuracy & relevanceState Machine

**Data Sources:** Azure Blob, Delta Lake, SQL

**Vector DBs:** Weaviate, FAISS, ChromaDB

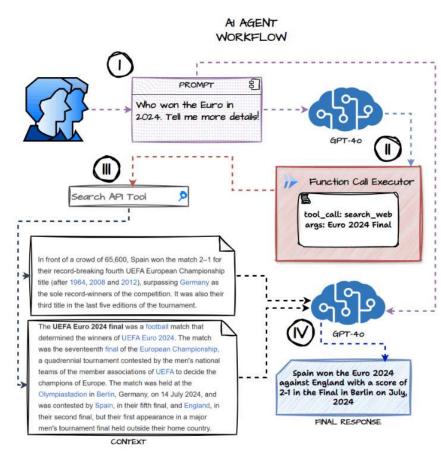
LLMs: OpenAl, MosaicML, Azure OpenAl

**Databricks Runtime:** Spark, MLFlow, Al Agents

# AGENTIC RAG

## Agentic RAG: Al That Thinks and Acts

- LLMs + Reasoning + Automation
  - → More than just text generation
- Context-aware Al agents that retrieve, analyze, and take action
- Refine responses with contextual reasoning
- Automate decision-making workflows



Source: Dipanjan Sarkar

# Types Of Al Agent

| Name of the agent                             | Key Characteristics   | Examples  | Best For   |
|---|---|---|--|
| Fixed Automation: The Digital Assembly Line   | No intelligence, predictable behavior, limited scope                | RPA, email<br>autoresponders, basic<br>scripts                    | Repetitive tasks,<br>structured data, no need<br>for adaptability                |
| LLM-Enhanced:<br>Smarter, but Not<br>Einstein | Context-aware, rule-<br>constrained, stateless                      | Email filters, content<br>moderation, support<br>ticket routing   | Flexible tasks, high-<br>volume/low-stakes, cost-<br>sensitive scenarios         |
| ReAct: Reasoning<br>Meets Action              | Multi-step workflows,<br>dynamic planning, basic<br>problem-solving | Travel planners, Al<br>dungeon masters,<br>project planning tools | Strategic planning, multi-<br>stage queries, dynamic<br>adjustments              |
| ReAct + RAG:<br>Grounded Intelligence         | External knowledge<br>access, low hallucinations,<br>real-time data | Legal research tools,<br>medical assistants,<br>technical support | High-stakes decisions,<br>domain-specific tasks,<br>real-time knowledge<br>needs |
| Tool-Enhanced: The<br>Multi-Taskers           | Multi-tool integration,<br>dynamic execution, high<br>automation    | Code generation tools, data analysis bots                         | Complex workflows requiring multiple tools and APIs                              |
| Self-Reflecting: The Philosophers             | Meta-cognition,<br>explainability, self-<br>improvement             | Self-evaluating systems,<br>QA agents                             | Tasks requiring accountability and improvement                                   |

## ReAct RAG –Reasoning +Action+ knowledge

| Feature        | Description   |
|----------------|---|
| Intelligence   | Employs a RAG workflow, combining LLMs with external knowledge sources (databases, APIs, documentation) for enhanced context and accuracy.        |
| Behavior       | Uses ReAct-style reasoning to break down tasks, dynamically retrieving information as needed. Grounded in real-time or domain-specific knowledge. |
| Scope          | Designed for scenarios requiring high accuracy and relevance, minimizing hallucinations.  |
| Best Use Cases | High-stakes decision-making, domain-specific applications, tasks with dynamic knowledge needs (e.g., real-time updates).                          |
| Examples       | Legal research tools, medical assistants referencing clinical studies, technical troubleshooting agents.  |

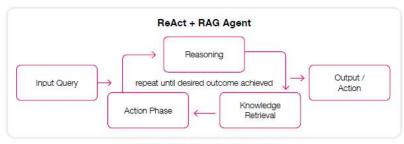
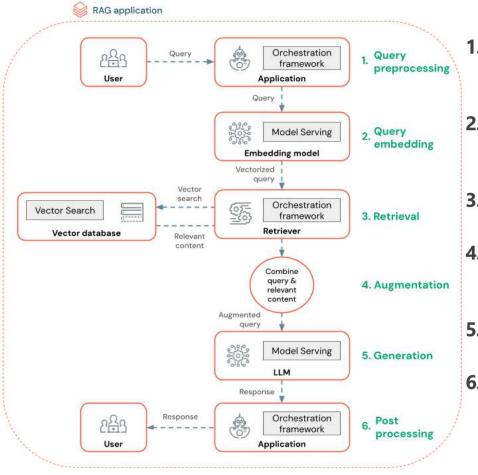


Fig 1.5: Workflow of a ReAct + RAG agent

Source:https://www.galileo.ai/ebook-mastering-agents

## Al Agents & RAG – Working Together



- Query Preprocessing The user query is formatted, templated, or keyword-extracted for vector search.
- 2. **Query Vectorization** Model Serving converts the query into embeddings, aligning with the indexed data.
- 3. **Retrieval Phase** A vector similarity search fetches and ranks the most relevant data chunks
- Prompt Augmentation Retrieved chunks are merged with the query to enhance context before LLM processing.
- LLM Generation The LLM generates a response using the enriched prompt
- **6. Post-processing** The output is refined with business logic, citations, or formatting adjustments.

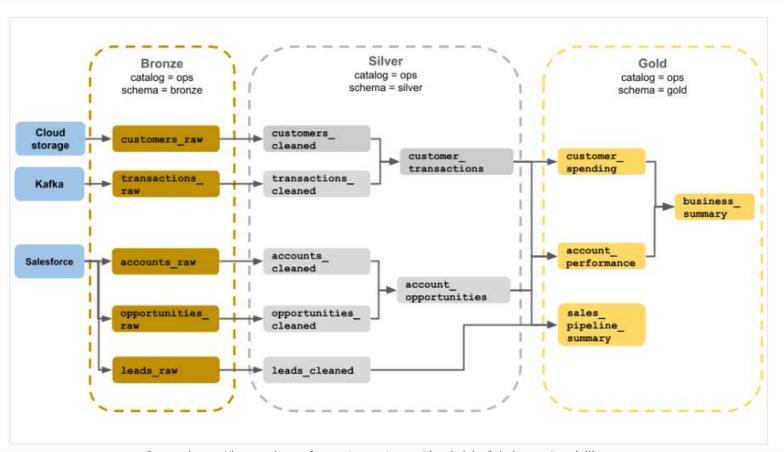
Source:https://www.galileo.ai/ebook-mastering-agents

# Implementing RAG Pipelines & Agents on Azure Databricks

#### AZURE DATABRICKS

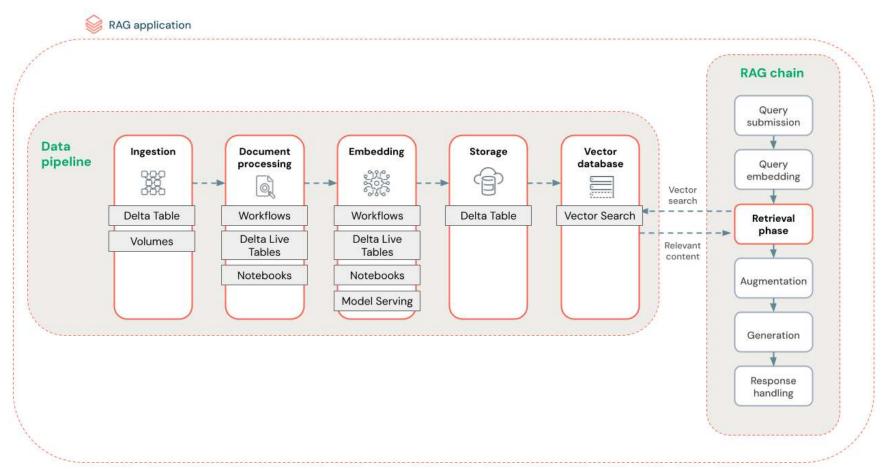
- Unified, open analytics platform for data, Al, and ML for data-driven decision-making
- Built on Apache Spark, optimized for Azure and integrated with cloud storage and security
- Uses Data Lakehouse + AI for optimized performance
- Supports ETL, ML, BI, & Generative AI.
- Data Governance & Security Manage access and compliance effortlessly with Unity Catalog for secure data control.
- Streaming & Real-time Analytics Process live data streams with Structured Streaming for instant insights and automation.

### Medallion Architecture



Source:https://learn.microsoft.com/en-us/azure/databricks/lakehouse/medallion

# RAG DATA Pipeline



Source: https://www.databricks.com/glossary/retrieval-augmented-generation-rag

## Real-time Use Cases & Best Practices

# Implementing RAG in Databricks

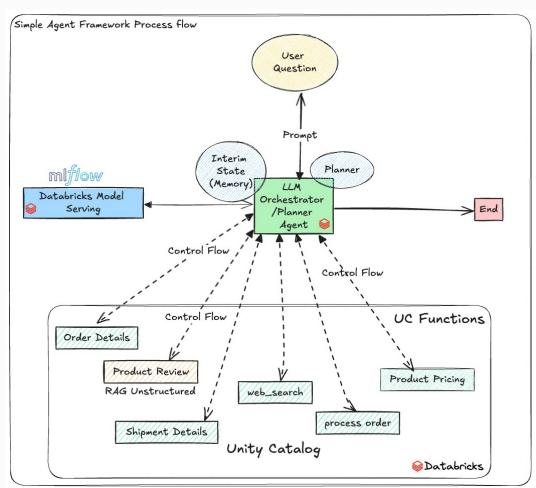
1.Ingest & Prepare Data: Store in Delta Lake or Azure Blob

2.**Generate Embeddings:** Use FAISS/ChromaDB for vector indexing

3. Retrieve Relevant Context: Query vector DB for relevant documents

4.Generate Responses: Pass retrieved data to LLM

5.Agent Execution: Automate insights & decision-making



Source: https://www.databricks.com/blog/announcing-mosaic-ai-agent-framework-and-agent-evaluation

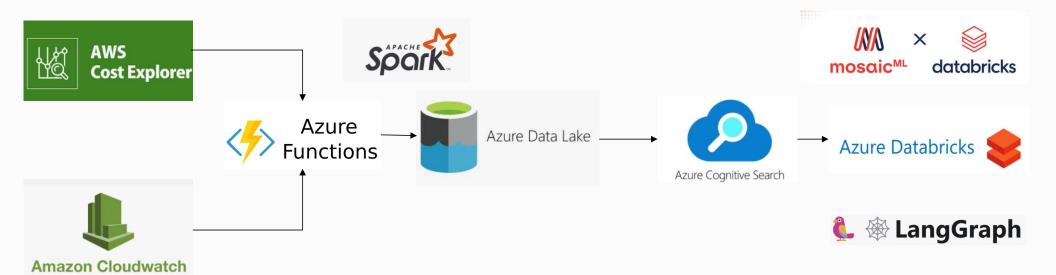
# FinOps Genie in Action

#### Use Case:

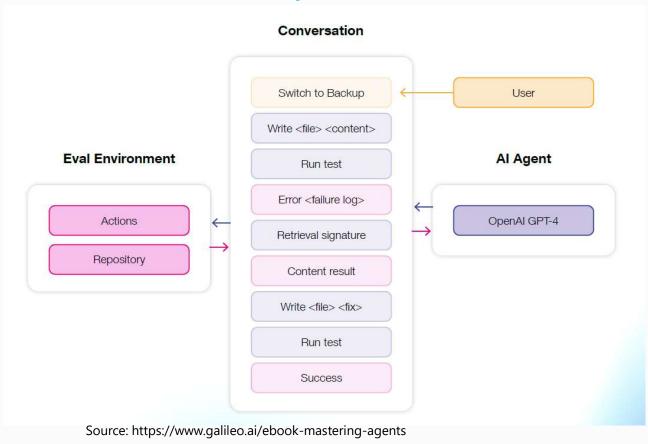
- AWS Cost Analysis & Optimization using RAG-based LLM Agent
- Ingest AWS cost data into Databricks
- Retrieve relevant insights using RAG
- Al Agent suggests cost-saving strategies



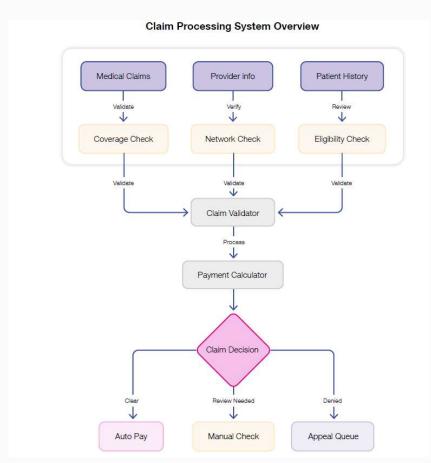
# Implementing RAG & AI Agents in Databricks

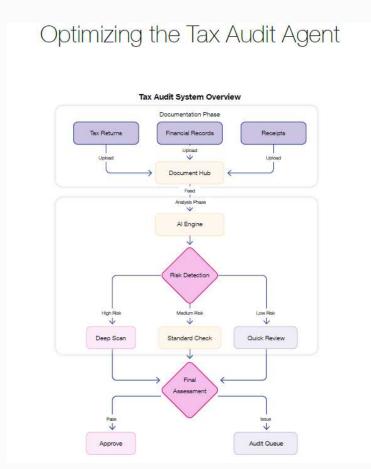


# Automated Al Agent driven Development



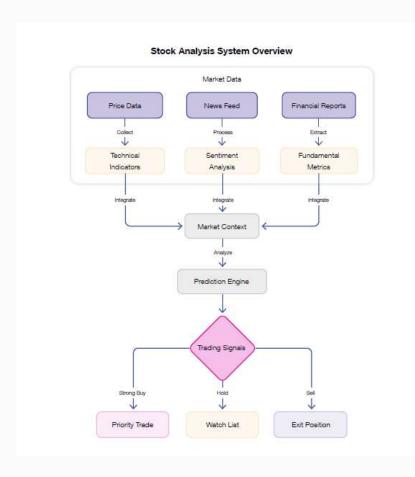
# Al Agents Usecases: Claim Processing

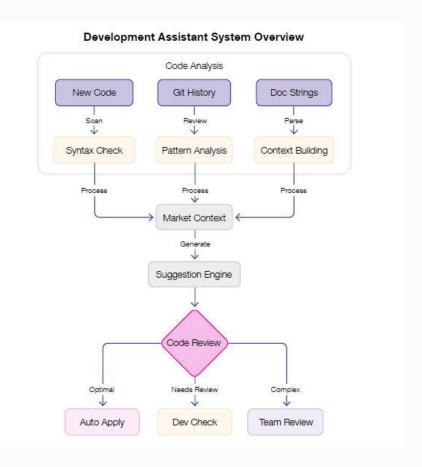




Source: https://www.galileo.ai/ebook-mastering-agents

# Al Agents Usecases: Stock Analysis





## **RAG & Al Agents in Enterprise**

- Financial Services: Risk analysis & fraud detection
- Cloud Cost Optimization: Al-powered costsaving recommendations
- Customer Support AI: Context-aware chatbot interactions
- Healthcare AI: Clinical data retrieval & summarization

## Databricks, Fabric & Synapse: UseCases

#### Comparison: Databricks vs. Fabric vs. Synapse

| Feature            | Azure Databricks 🛑                          | Microsoft Fabric                                    | Azure Synapse Analytics                        |
|--------------------|---|---|--|
| Core Focus         | Al, ML, Data Engineering<br>& Analytics     | Unified Data & Al Platform                          | Data Warehousing & Big<br>Data Analytics       |
| Architecture       | Open Lakehouse (Delta<br>Lake)              | SaaS-based Lakehouse                                | SQL Data Warehouse & Data<br>Lake              |
| Best For           | Big Data, ML, Al, Real-time<br>Streaming    | End-to-end Data & AI (BI, AI,<br>Governance)        | BI, SQL Analytics, ETL                         |
| Compute<br>Engine  | Apache Spark, Photon                        | Power BI, Spark                                     | SQL Pools, Apache Spark                        |
| Data<br>Processing | Batch, Streaming, ML, Al                    | Low-code/no-code, Al-<br>powered automation         | SQL-based ETL, Data<br>Pipelines               |
| Storage            | Delta Lake (open format)                    | OneLake (Fabric's data lake)                        | Azure Data Lake Storage<br>(ADLS)              |
| Governance         | Unity Catalog (fine-<br>grained access)     | Microsoft Purview                                   | Role-based Access Control<br>(RBAC)            |
| BI &<br>Reporting  | Connects to Power BI                        | Deep Power BI integration                           | Power BI & SQL Reporting                       |
| Use Cases          | AI/ML, Real-time<br>Analytics, Data Science | Business Intelligence, Al<br>Automation, Governance | Data Warehousing,<br>Structured Data Analytics |

# Best Practices for Scalable RAG & Al Agents

- Optimize Retrieval Efficiency: Hybrid search (semantic + keyword)
- Fine-tune models for domain-specific knowledge using Azure OpenAl, MosaicML, or Databricks Foundation Models.
- Implement Cohere Reranking for improved relevance in retrieval results.
- Optimize embedding model selection (e.g., OpenAl's ada-002, Cohere embeddings).
- Reduce Hallucinations: Reinforcement learning for feedback loops
- Scalability Considerations: Deploy RAG with Databricks & Azure Al
- Implement AI Agent Evaluation Framework to measure response accuracy and quality.

# Future of RAG & Al Agents

- Memory-augmented Agents (Retain past interactions)
- Autonomous Al Decision-Making (Selfimproving models)
- Advanced Multi-Agent Systems (Collaboration between Al agents)







