

INTRODUCTION

Agentic RAG

When Retrieval Meets Reasoning

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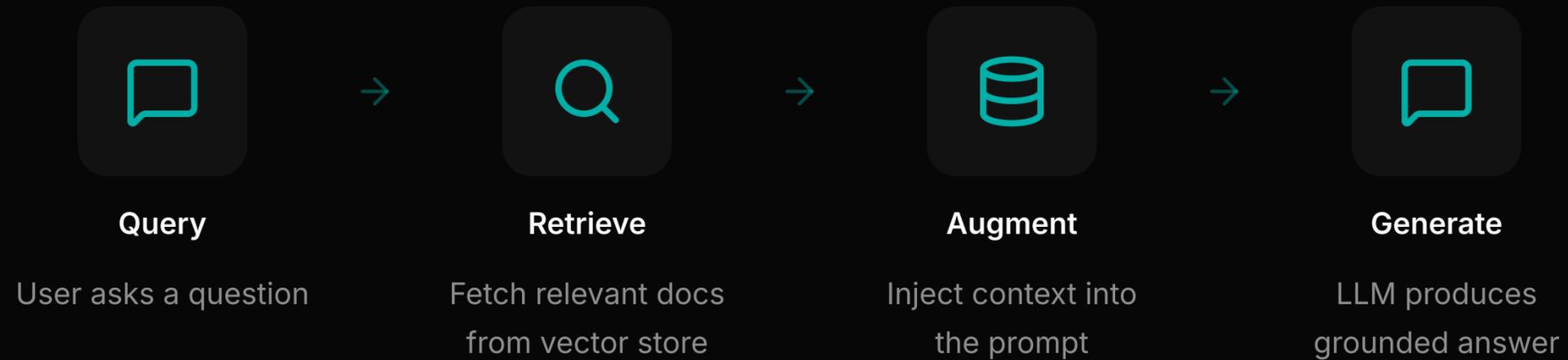
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Agenda

- 01** RAG Recap & Limitations
- 02** What is Agentic RAG?
- 03** Architecture & Design Patterns
- 04** Research Landscape
- 05** Frameworks & Tools
- 06** Advantages, Challenges & Use Cases
- 07** Getting Started

Retrieval-Augmented Generation

The standard pattern: retrieve external knowledge to ground LLM responses



Key insight: RAG bridges the gap between parametric knowledge (training data) and non-parametric knowledge (external documents), reducing hallucination.

Limitations of Traditional RAG



One-Shot Retrieval

Single query, single retrieval pass. No ability to evaluate or re-retrieve if results are poor.



Single Data Source

Typically limited to one vector store. Cannot combine structured data, APIs, and documents.



No Self-Correction

Cannot assess retrieval quality. Garbage in, garbage out -- no validation loop.



Static Strategy

Same retrieval approach for every query. Cannot adapt to query complexity or type.



Agentic RAG makes reasoning an integral part of retrieval.

Instead of blindly retrieving and generating, the system reasons about what to retrieve, evaluates what it found, and decides what to do next.

Reflection

Planning

Tool Use

Multi-Agent

Traditional RAG vs Agentic RAG

TRADITIONAL RAG

WORKFLOW

Fixed linear pipeline

DECISION-MAKING

Static rules

DATA SOURCES

Single vector store

COMPLEX QUERIES

Struggles with multi-hop

SELF-VALIDATION

None

ADAPTABILITY

Same strategy always

AGENTIC RAG

WORKFLOW

Dynamic, iterative reasoning loop

DECISION-MAKING

Agent decides what/where/how

DATA SOURCES

Multiple KBs, APIs, tools

COMPLEX QUERIES

Decomposes into sub-tasks

SELF-VALIDATION

Scores & re-retrieves

ADAPTABILITY

Adapts in real-time

Key Architectural Patterns

Taxonomy from Singh et al. (2025)



Single-Agent (Router) Simple

One agent manages routing, retrieval, and integration. Centralizes decision-making across multiple knowledge sources.



Multi-Agent Scalable

Specialized agents work in parallel: orchestrator coordinates, router directs queries, researchers retrieve and analyze.



Hierarchical Layered

Multi-tiered agent structure. Top-tier handles strategic decisions, lower-tier agents execute retrieval tasks.



Corrective & Adaptive Self-correcting

Evaluates relevance of retrieved docs, refines queries iteratively. Adaptive variant routes by query complexity.

Source: Singh et al., "Agentic Retrieval-Augmented Generation: A Survey on Agentic RAG" (2025) · [arXiv:2501.09136](https://arxiv.org/abs/2501.09136)

The Four Pillars of Agentic RAG



Reflection

Agent evaluates its own outputs and retrieval quality, triggering re-retrieval when results are insufficient.

Self-RAG, CRAG



Planning

Creates a step-by-step plan before executing retrieval. Decomposes complex queries into sub-tasks.

Query decomposition



Tool Use

Calls external tools -- search engines, calculators, APIs, code interpreters -- beyond simple vector retrieval.

Function calling

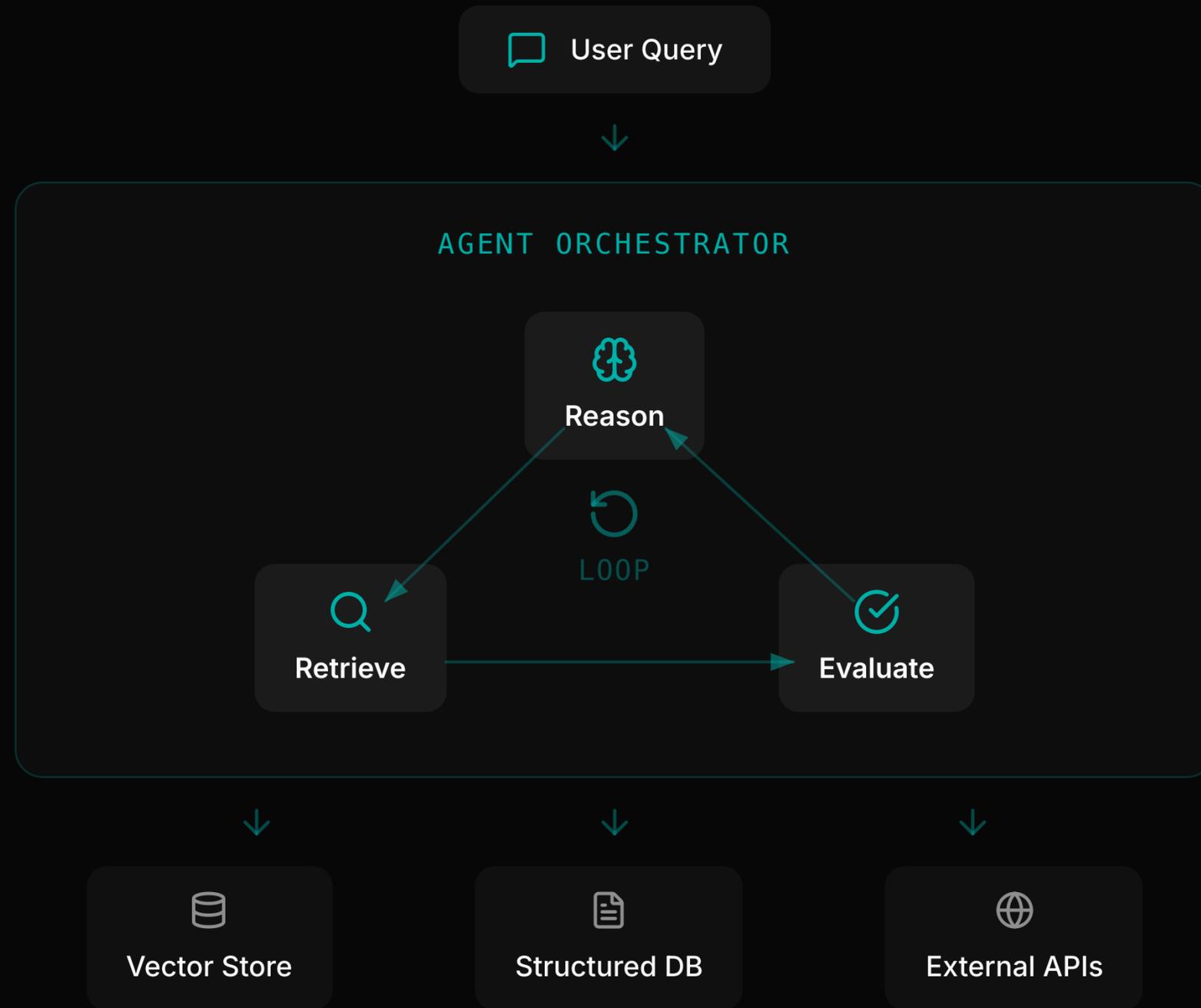


Multi-Agent Collaboration

Multiple specialized agents with different roles work together on complex information needs.

Manager/worker

Agentic RAG Architecture



Key Papers

Jan 2025	Agentic RAG: A Survey Singh et al.	Foundational survey	arXiv:2501.09136
Oct 2023	Self-RAG: Self-Reflection for RAG Asai et al.	Key precursor	arXiv:2310.11511
Feb 2026	A-RAG: Hierarchical Retrieval Interfaces Du et al.	Scaling patterns	arXiv:2602.03442
Jul 2025	RAG-Reasoning with Deep Reasoning Li et al.	Reasoning integration	arXiv:2507.09477
Jun 2025	Reasoning RAG: System 1 vs System 2 Liang et al.	Industry focus	arXiv:2506.10408
Aug 2025	Agentic Hybrid RAG for Science Nagori et al.	GraphRAG + VectorRAG	arXiv:2508.05660

Also notable: Corrective RAG (CRAG), Adaptive-RAG, Tiny-Critic RAG (2603.00846), and RAG for Fintech (2510.25518).

Trade-offs

✓ What You Gain

Higher Accuracy Through Iteration

Self-RAG: 55.8% on PopQA vs 14.7% base model.

Multi-Hop Reasoning

Refines retrieval based on intermediate insights.

Heterogeneous Sources

Vector stores, SQL, APIs, and knowledge graphs in one query.

Adaptive Routing

Routes by complexity: direct generation, single-step, or multi-step.

⚠ What It Costs

Latency

Each iteration adds another LLM call.

Cost

3-10x increase vs traditional RAG.

Reliability

Agent loops can fail without proper guardrails.

Observability

Multi-step pipelines are harder to debug.

Sources: [Asai et al. \(2023\)](#) · [Singh et al. \(2025\)](#)

Real-World Use Cases



Customer Support **66% of queries handled**

Salesforce Agentforce at Fisher & Paykel. The survey also cites Twitch's ad sales system on Amazon Bedrock for campaign and audience retrieval.



Healthcare **68% → 73% accuracy**

Clinical decision support integrating health records with medical literature. Radiology QA improved across 24 LLMs with agentic retrieval.



Scientific Research **Hybrid RAG selection**

Dynamic selection between GraphRAG and VectorRAG per query. Also: research paper synthesis with enriched citations across domains.



Personal AI Assistants **Most widespread today**

AI coding tools (Cursor, Claude Code) and workspace assistants (Copilot, Notion AI) use agentic retrieval across local files, codebases, and web.

Sources: [Singh et al. \(2025\)](#) · [Salesforce](#) · [arXiv:2508.00743](#) · [Nagori et al. \(2025\)](#)

KEY TAKEAWAYS

1. Agentic RAG transforms retrieval from a static lookup into a dynamic reasoning loop.
2. Start simple — make reasoning part of retrieval. Add evaluation first, then iterative re-retrieval, then additional sources.
3. Agentic RAG adds latency, cost, and complexity. Use it when queries require multi-step reasoning or cross-source synthesis — not as a default upgrade.



Questions?

Let's discuss.

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