From **Retrieval** to **Action**:

How RAG Unlocks Enterprise AI

Christian Zaccaria

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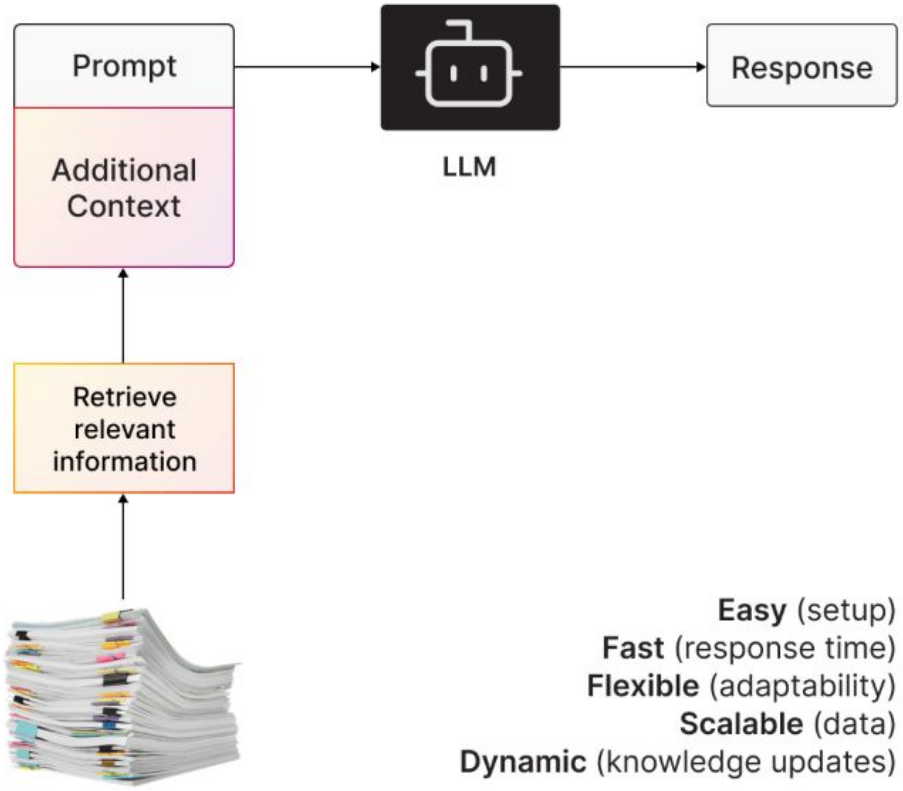
Red Hat

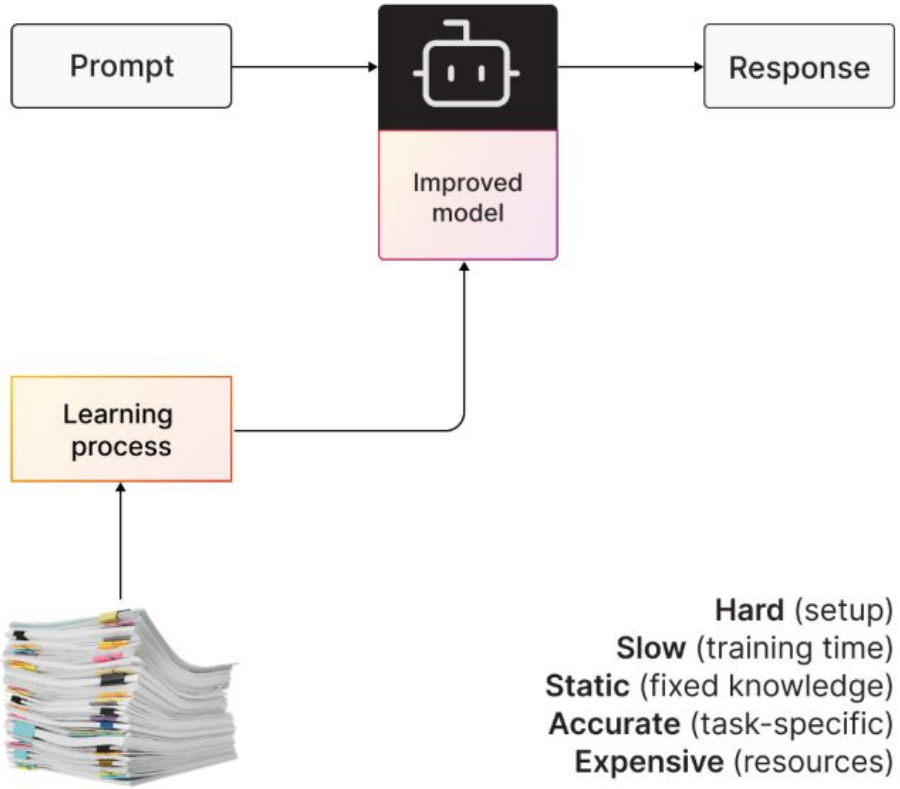
Why RAG instead of Fine Tuning?

Retrieval-augmented generation (RAG)



Easy (setup)
Fast (response time)
Flexible (adaptability)
Scalable (data)
Dynamic (knowledge updates)

Fine-tuning the Model



Hard (setup)
Slow (training time)
Static (fixed knowledge)
Accurate (task-specific)
Expensive (resources)

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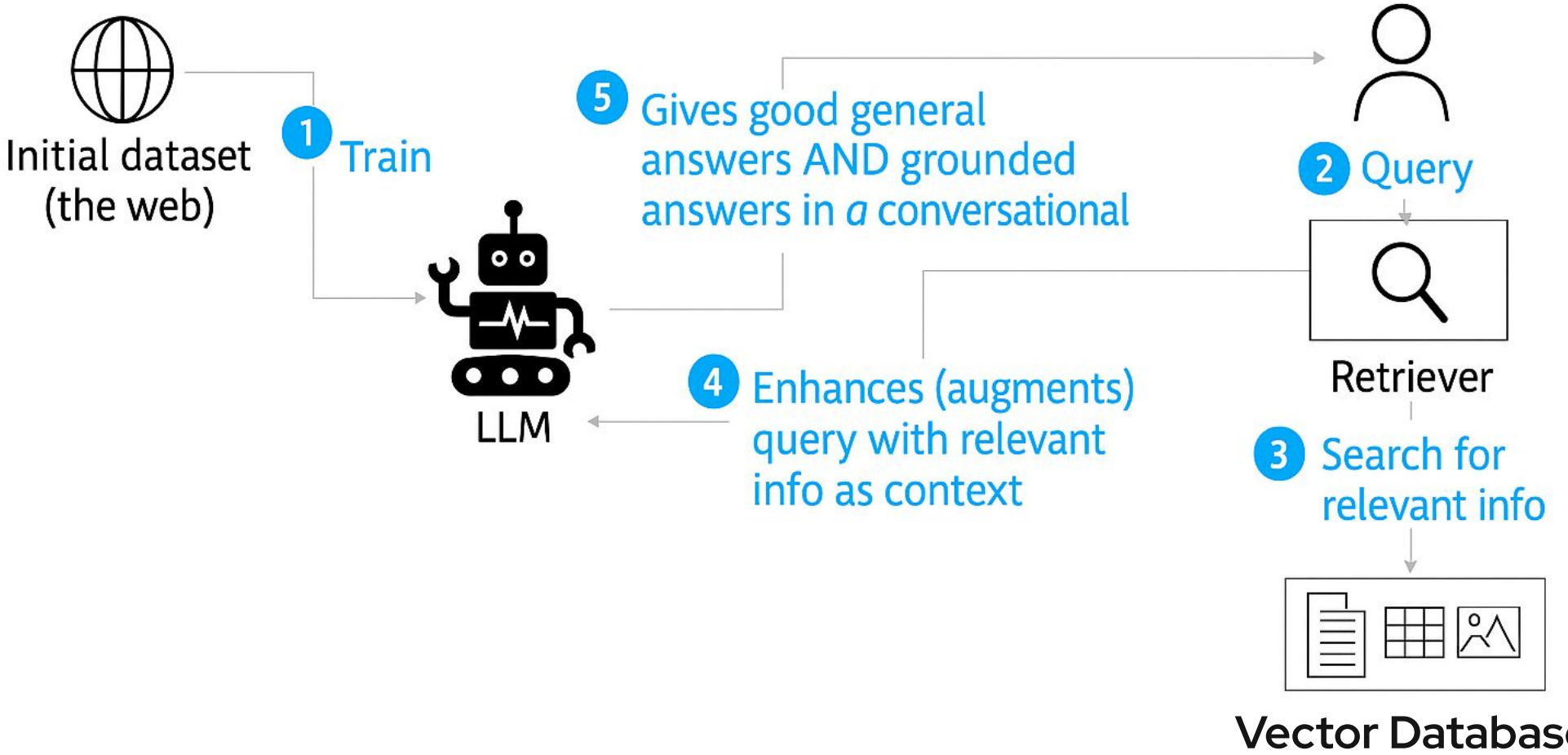
How does RAG work?



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Concept: Text Chunking

Chunk Size:

The maximum length of text to include in a chunk.

Balanced chunk size preserves context and precision.

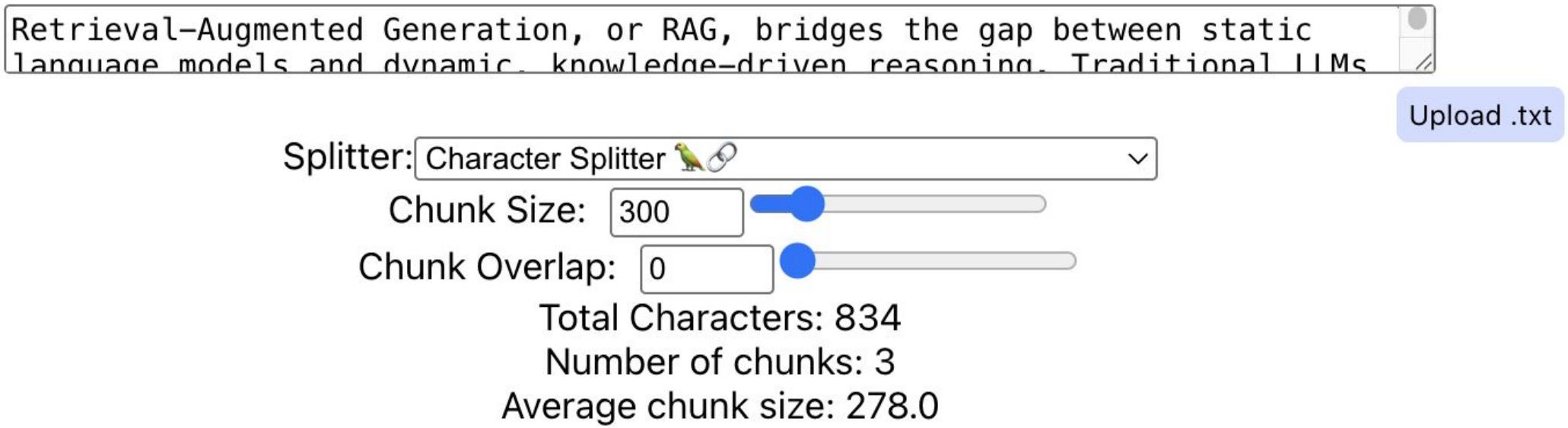
Typically measured in tokens.

Chunk Overlap Size:

Adds small amount of overlapping text between consecutive chunks.

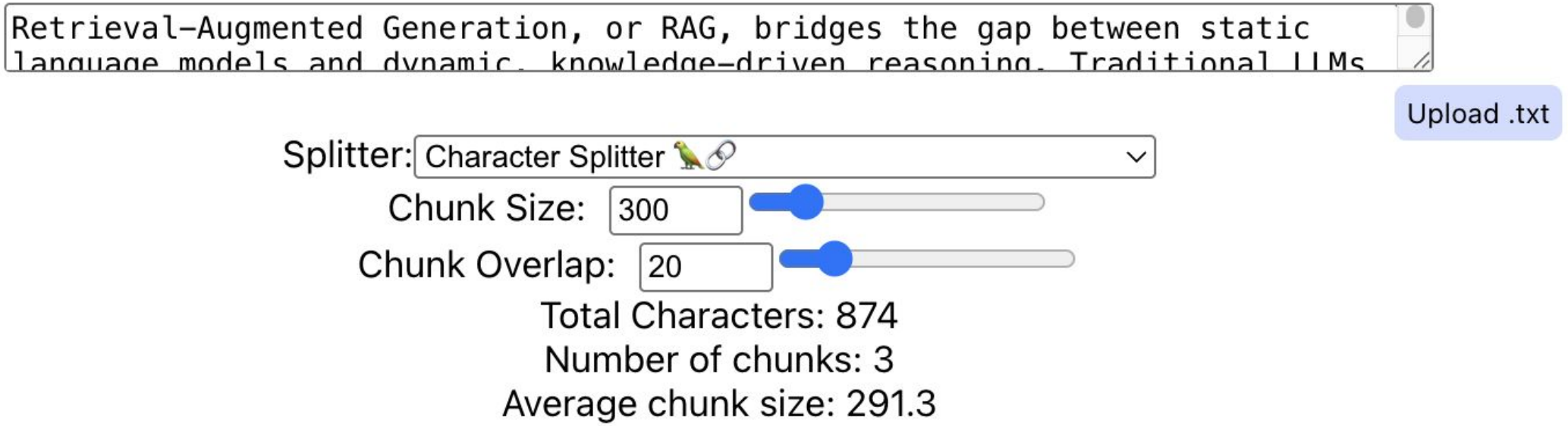
Helps preserve continuity.

Text Chunking example



Retrieval-Augmented Generation, or RAG, bridges the gap between static language models and dynamic, knowledge-driven reasoning. Traditional LLMs generate answers based on patterns learned during training, but their knowledge becomes stale the moment training ends. This can be overcome thanks to RAG. This makes responses more accurate, current, and context-aware without retraining the model itself. The process depends on embedding models that convert both user queries and documents into vector representations stored in a vector database. When a query is made, the RAG system retrieves the most semantically similar chunks, which are appended to the prompt before generation. This design decouples reasoning from stored knowledge, enabling smaller models to compete with much larger ones while dramatically lowering compute costs.

Text Chunking example



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Concept: Embedding Models

Purpose:

- Capture semantic meaning for accurate retrieval and insertion.
- Convert text chunks to embeddings.

Benefits:

- Enables semantic search.
- Makes LLMs context-aware beyond their training data.

Limitations:

- Dependant on the quality of the embedding model.

Embedding Models

Model	Nomic Embed	OpenAI Embeddings
Size	Smaller (768-dim)	Larger (1,536-dim)
Cost	Free, runs locally	Pay-per-token (API-based)
Accuracy	Strong semantic accuracy	Good, but not always top-performing
Latency	Very fast (no API call)	Higher (network latency)
Efficiency	Dense, compact vectors	Larger, sometimes redundant vectors
Best for	Local, cost-efficient RAG	Maximum semantic coverage

Vector Embeddings example

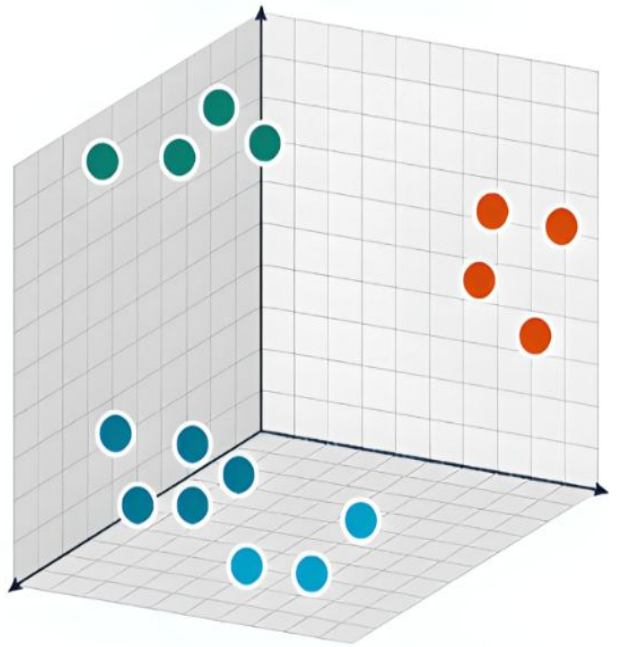
4 documents
- Landscapes
- Dogs
- Food
- Cats

Text Chunks

VECTOR EMBEDDING

[0.95, 0.49, 0.67, 0.75, 0.43, 0.00, 0.60, 0.13, 0.72, ...],
[0.73, 0.83, 0.80, 0.48, 0.55, 0.83, 0.86, 0.85, 0.06, ...],
[0.03, 0.71, 0.62, 0.07, 0.74, 0.30, 0.80, 0.08, 0.63, ...],
[0.49, 0.48, 0.38, 0.51, 0.45, 0.05, 0.10, 0.92, 0.29, ...],
[0.84, 0.38, 0.81, 0.00, 0.48, 0.61, 0.41, 0.85, 0.93, ...],
[0.24, 0.90, 0.69, 0.57, 0.43, 0.60, 0.37, 0.63, 0.28, ...],
[0.72, 0.33, 0.36, 0.98, 0.88, 0.05, 0.64, 0.91, 0.15, ...],
[0.89, 0.17, 0.44, 0.78, 0.33, 0.59, 0.29, 0.23, 0.22, ...],
[0.88, 0.75, 0.38, 0.77, 0.31, 0.98, 0.84, 0.79, 0.25, ...],
[0.11, 0.77, 0.30, 0.56, 0.62, 0.14, 0.89, 0.19, 0.62, ...],
[0.63, 0.41, 0.97, 0.73, 0.64, 0.41, 0.96, 0.36, 0.87, ...],
[0.51, 0.16, 0.26, 0.94, 0.53, 0.38, 0.39, 0.90, 0.55, ...],
[0.91, 0.99, 0.10, 0.87, 0.24, 0.91, 0.94, 0.36, 0.69, ...],
[0.89, 0.64, 0.14, 0.94, 0.51, 0.24, 0.61, 0.99, 0.11, ...],
[0.77, 0.65, 0.48, 0.94, 0.49, 1.00, 0.24, 0.10, 0.97, ...],
[0.58, 0.47, 0.01, 0.56, 0.59, 0.32, 0.79, 0.95, 0.40, ...]

VECTOR DATABASE



Vector Embeddings example

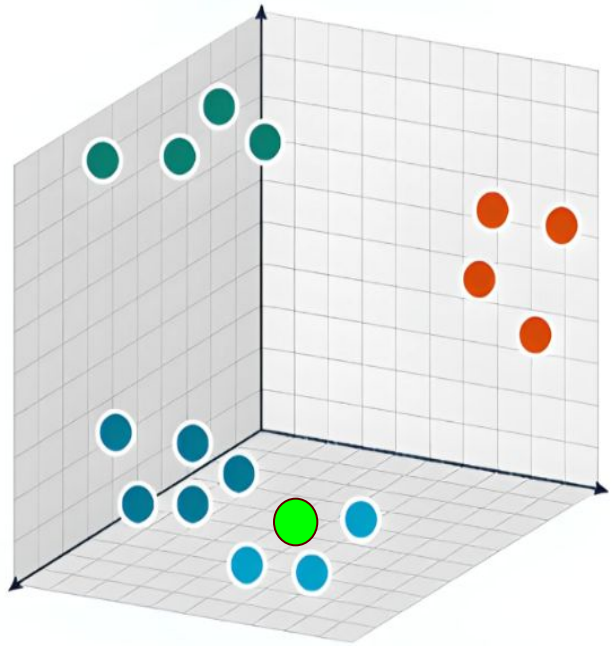
User Query

Give me information about a Poodle

VECTOR EMBEDDING

[0.24, 0.90, 0.69, 0.57, 0.43, ...]

VECTOR DATABASE



Approximate Nearest Neighbor (ANN)

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Vector Databases - Search Modes

Query: I would like information about a **pet**?

Search Modes:

Keyword search: exact terms present.

(Pet == Pet)

Vector search: based on semantic similarity in embedding space.

(Pet == Pet) or (Pet == Dog) or (Pet == Cat)

Hybrid search: combines both using a weighting factor (e.g. alpha).

$$\text{hybrid\_score} = \alpha \times \text{lexical\_score} + (1-\alpha) \times \text{vector\_score}$$

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How are the scores calculated?

Keyword search -> BM25

$$score(D,Q) = \sum_{i=1}^{n} IDF(q_i) \times \frac{f(q_i,D) \times (k_1+1)}{f(q_i,D) + k_1 \times (1 - b + b \times \frac{|D|}{avgdl})}$$

Term frequency ($f(q_i, D)$): rewards documents that mention the query term more often.

Inverse document frequency (IDF): boosts rare, informative terms and downplays common ones.

Document length normalization (|D|, avgdl, b): prevents long documents from being unfairly favored.

The constants k_1 and b control how strongly frequency and length affect the score, producing a balanced measure of how relevant each document is to the query.

How are the scores calculated?

Vector search -> Cosine Similarity, dot product

$$cosine\_similarity(q, d) = \frac{q \cdot d}{||q||\,||d||}$$

Dot Product (q · d): measures the angle of alignment between the query vector (q) and a document vector (d).

Vector Magnitude (||q|| and ||d||): represents the length of each vector.

How are the scores calculated?

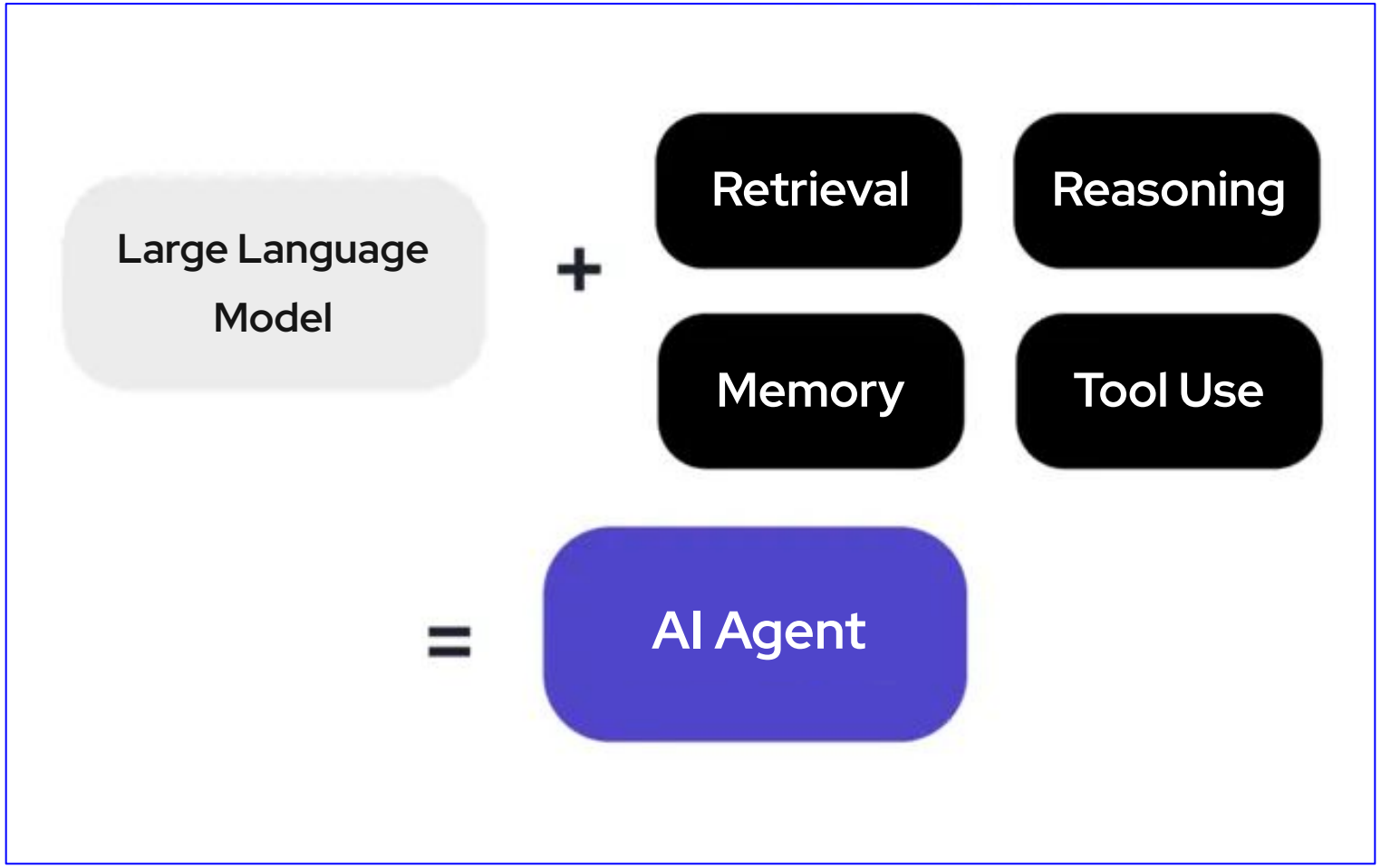
Hybrid Search -> Vector Search + Keyword Search

$$\text{hybrid\_score} = \alpha \times \text{lexical\_score} + (1-\alpha) \times \text{vector\_score}$$

- **Vector Search Score**
- **Keyword Search Score**
- **α (alpha):** determines the relative importance of each search type.

Concept: AI Agents

Query → Agent decision → Tool(s) → Response.



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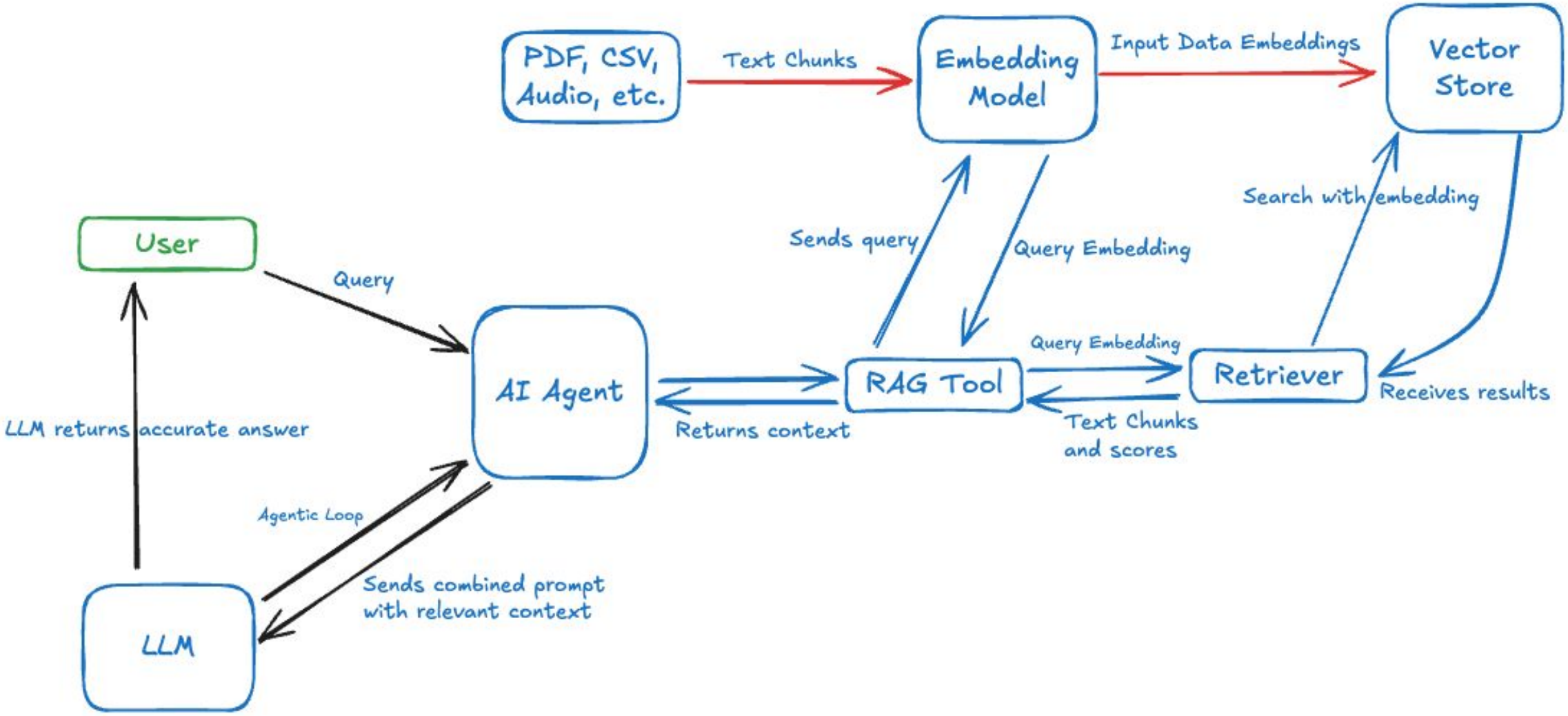
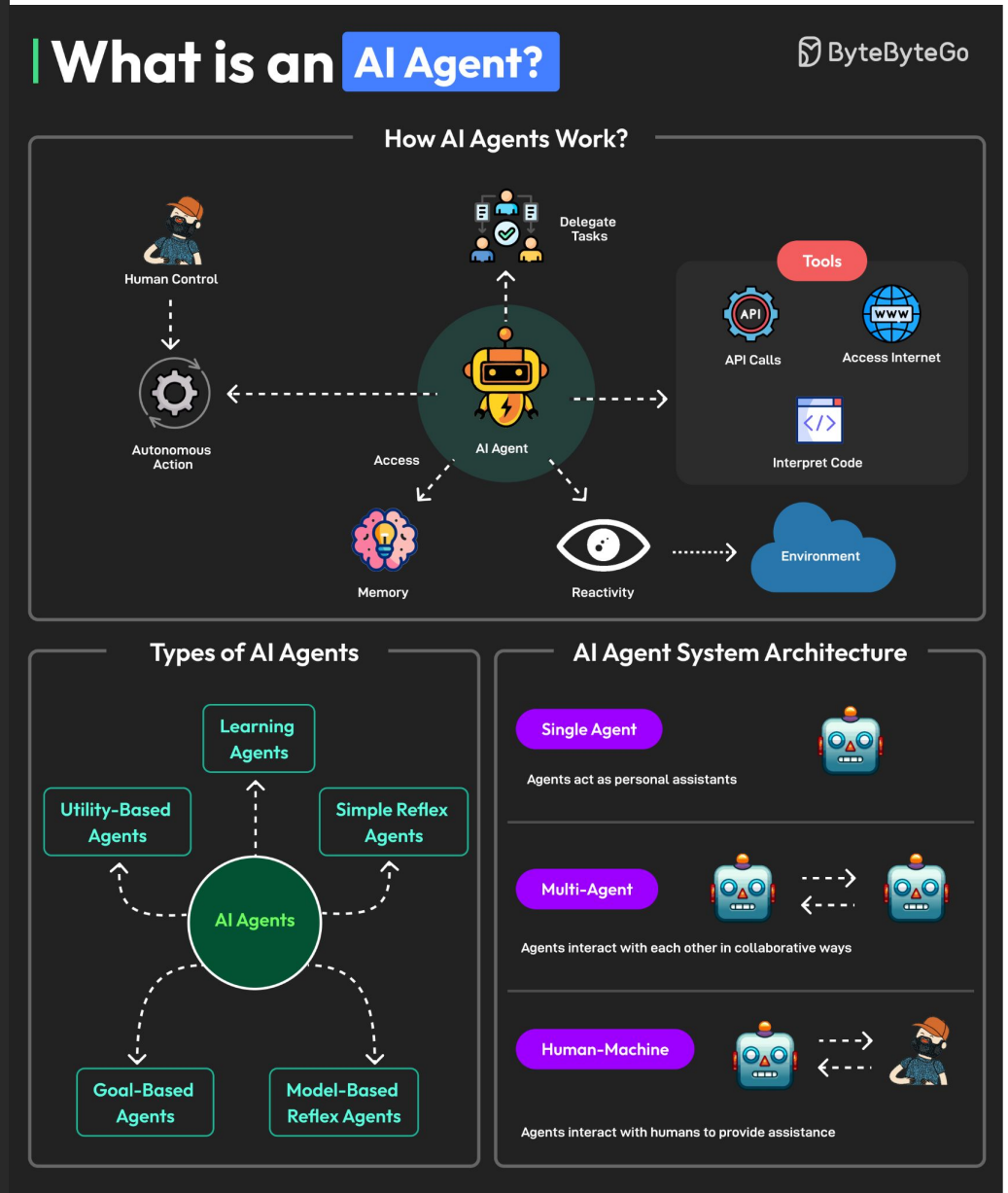
Joining them together



Building AI Agents

From OpenAI to Open Source

What's an AI Agent?



- An AI Agent is more than a chatbot — it's a system that can reason, access tools, remember context, and act.
- Typical loop:
  a. User request
  b. Reasoning & planning (LLM)
  c. Tool or API calls
  d. Context update (memory, DB)
  e. Response back to user
- An agent can perform autonomous actions without constant human intervention

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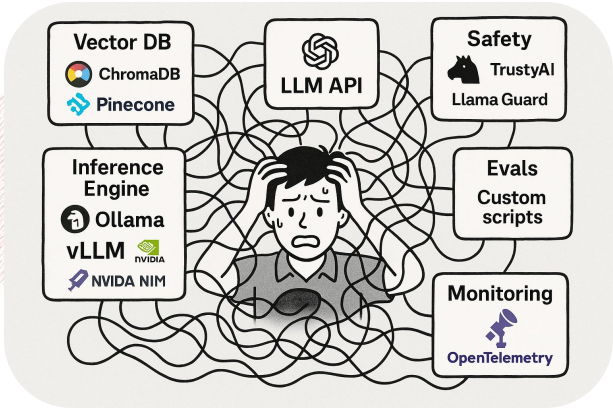
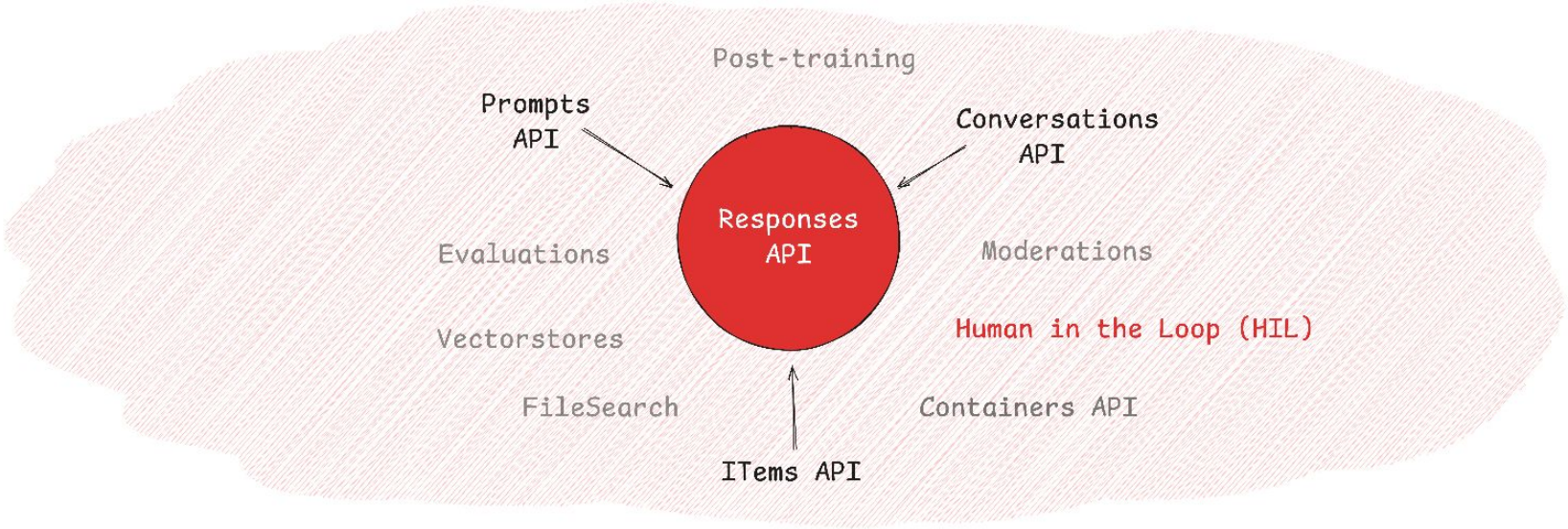
How Agents **SHOULD** be built!





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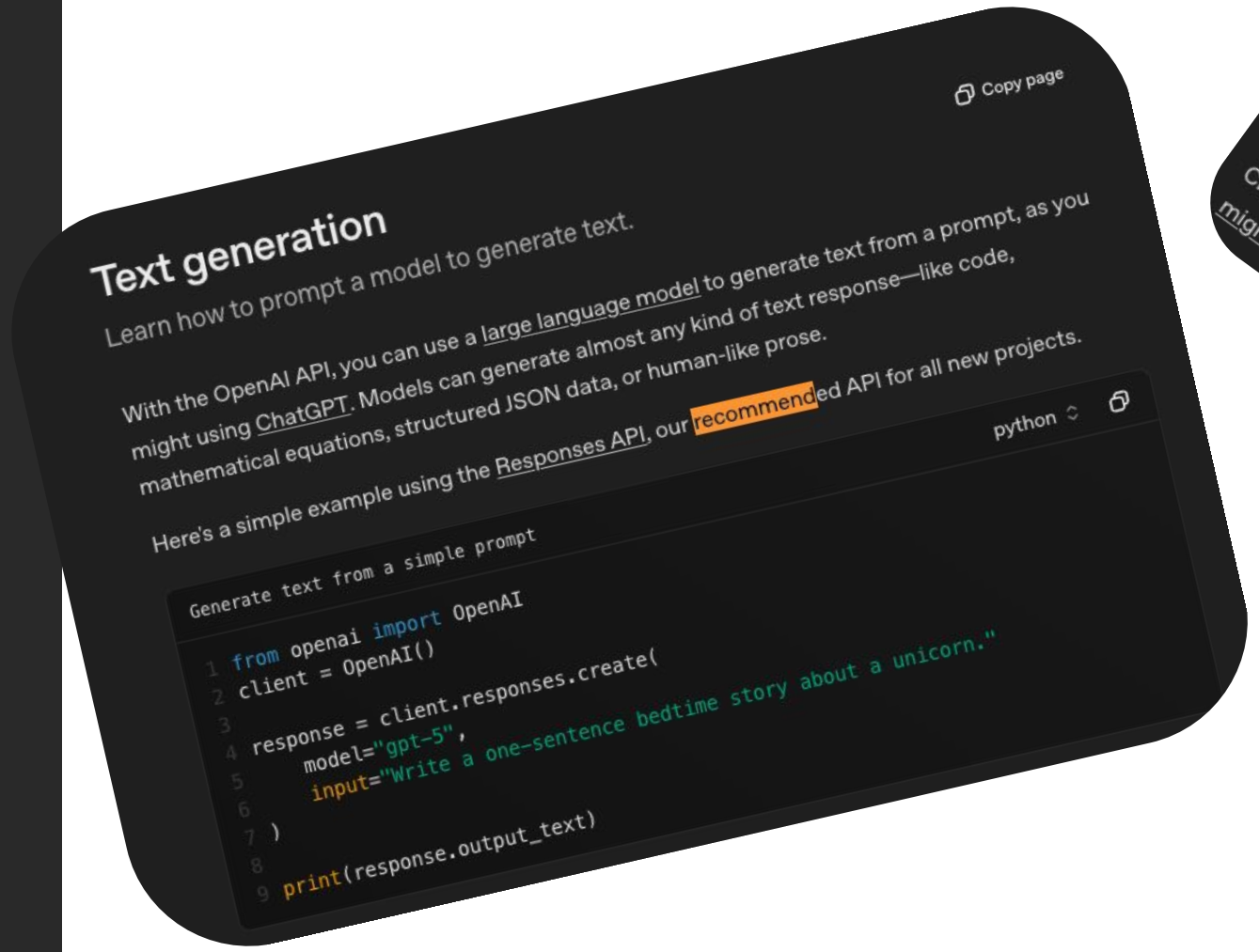
What is **OpenAI** Recommending?



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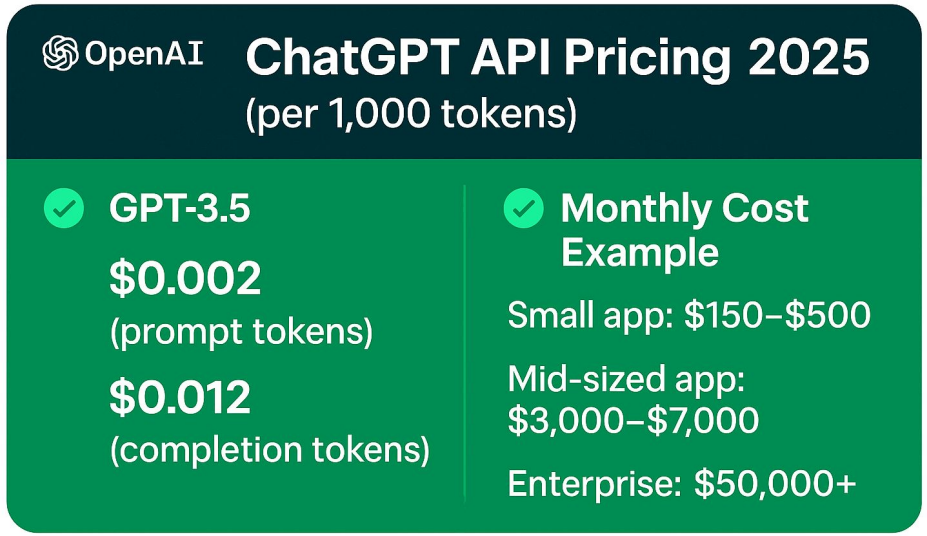
The OpenAI Ecosystem (Paid by Token)

- Easy to start — use ChatGPT, GPT-4 Turbo, or GPT-4o via API.
- Ecosystem: OpenAI APIS, embeddings, file storage, function calling.

- Cons:
  - **Costs scale with usage**
  - **Private data leaves your control**
    - Enterprises often hesitate to send data to external APIs.
  - Vendor lock in!



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But what if...

- But what if you just want to **experiment**?
- But what if you're building a local project or student **prototype**?
- But what if you want to create a Proof-of-Concept (**PoC**) for your company?
- But what if you're launching a **small startup** with limited budget?
- But what if you simply don't want to pay token costs while **testing**?
- But what if you are working with sensitive **private information** data?

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The Open Source Ecosystem

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Hosting Open-Source Models – Introducing Ollama

- **Ollama** lets you run large language models **locally or on-prem**.
- Think of it as *Docker for AI Models*.
- Models are pulled with commands like `ollama pull llama3` and run with `ollama run llama3`.
- Supports **Mac, Windows, Linux**.
- Integrates easily via HTTP API.

Free / Open-weight models you can self-host

Model	Developer	Description / Use Case
Granite-8B.Code-Instruct	IBM	Open-weight 8B model optimized for code generation, explan… software reasoning.
Llama 3 (8B / 70B)	Meta AI	General-purpose chat & reasoning model… support.
Gemma 2 (9B)	Google DeepMind	Lightweight, high-quality… …asks.
Mistral 7B / Mixtral 8×22B	Mistral AI	Efficie… …e-of-experts) for dialogue and
Phi-3 Mini (3.8B)	Mi…	…model for fast local inference and PoCs.
Qwen 2.5 (7B / 32…		…Multimodal (text + image) family with strong reasoning and long context.
	IBM	IBM's open embedding model for RAG, retrieval, and vector search applications.

Ok, I have a model and now what?

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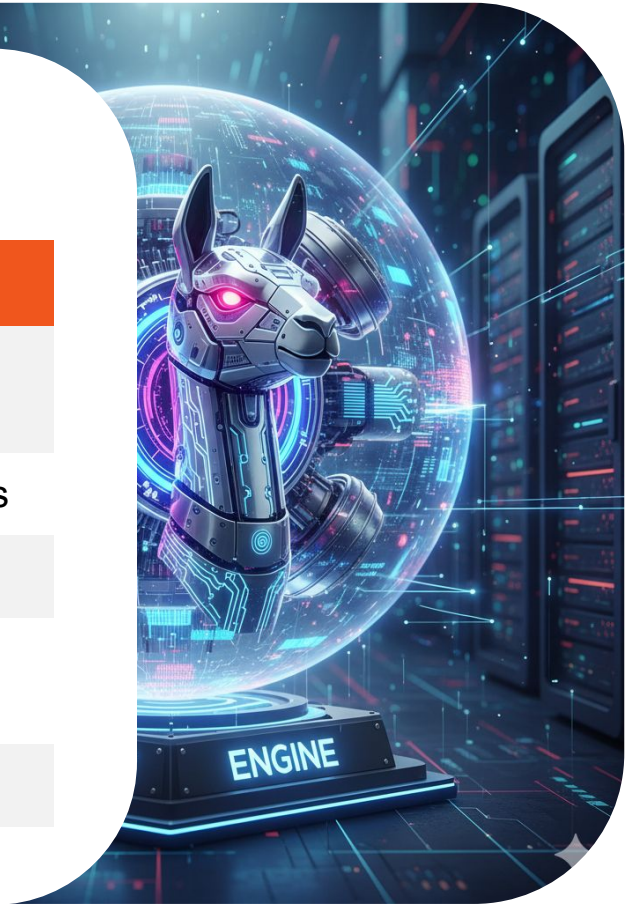
Introducing Llama Stack - The AI Engine

- *Llama Stack is to AI containers.*
- Open framework fr LLM-based app de
- Abstracts compone safety, telemetry
- Works with multiple vLLM, etc.)

Why Llama Stack?

Problem	Solution
Expensive SaaS LLMs	Bring your own models
Hard model switching	Pluggable inference providers
No safety	Guardrails and policy layer
Orchestration pain	Integrated agents, memory, tools
Lack of monitoring	Built-in evaluation/telemetry



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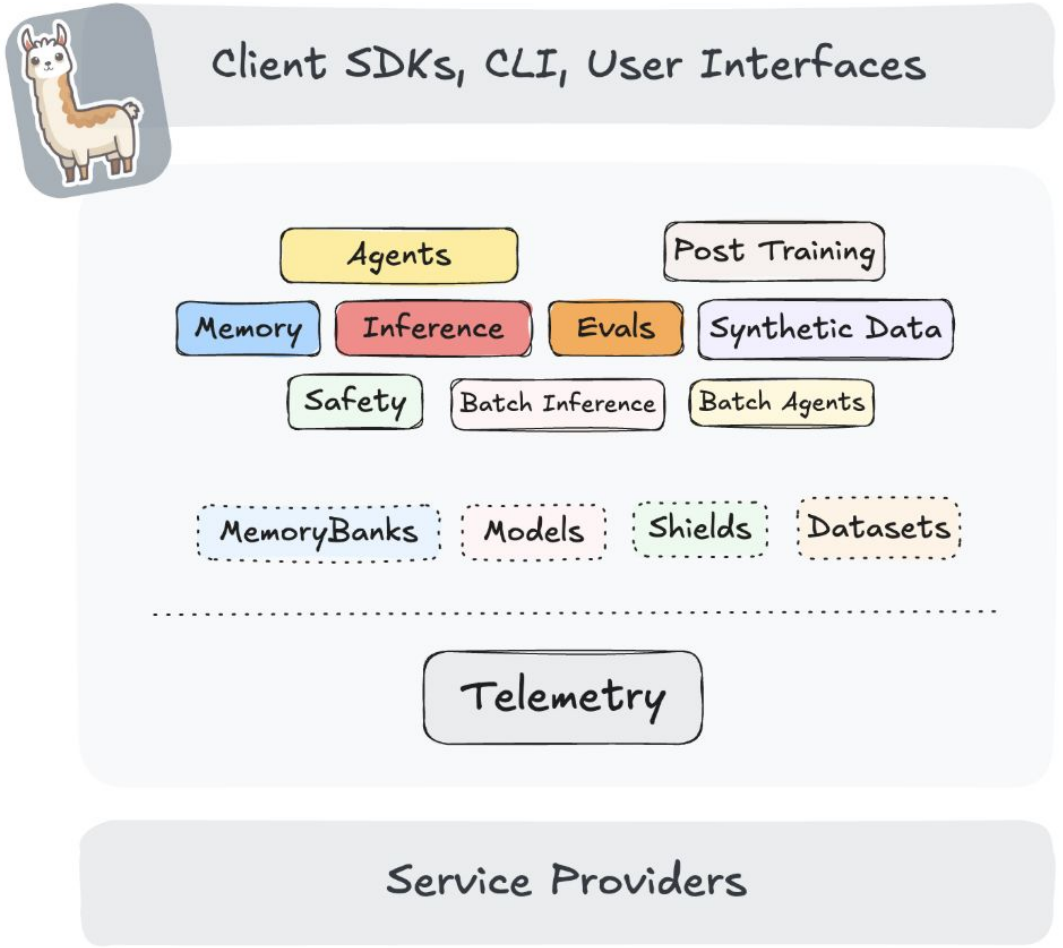
Llama Stack Architecture

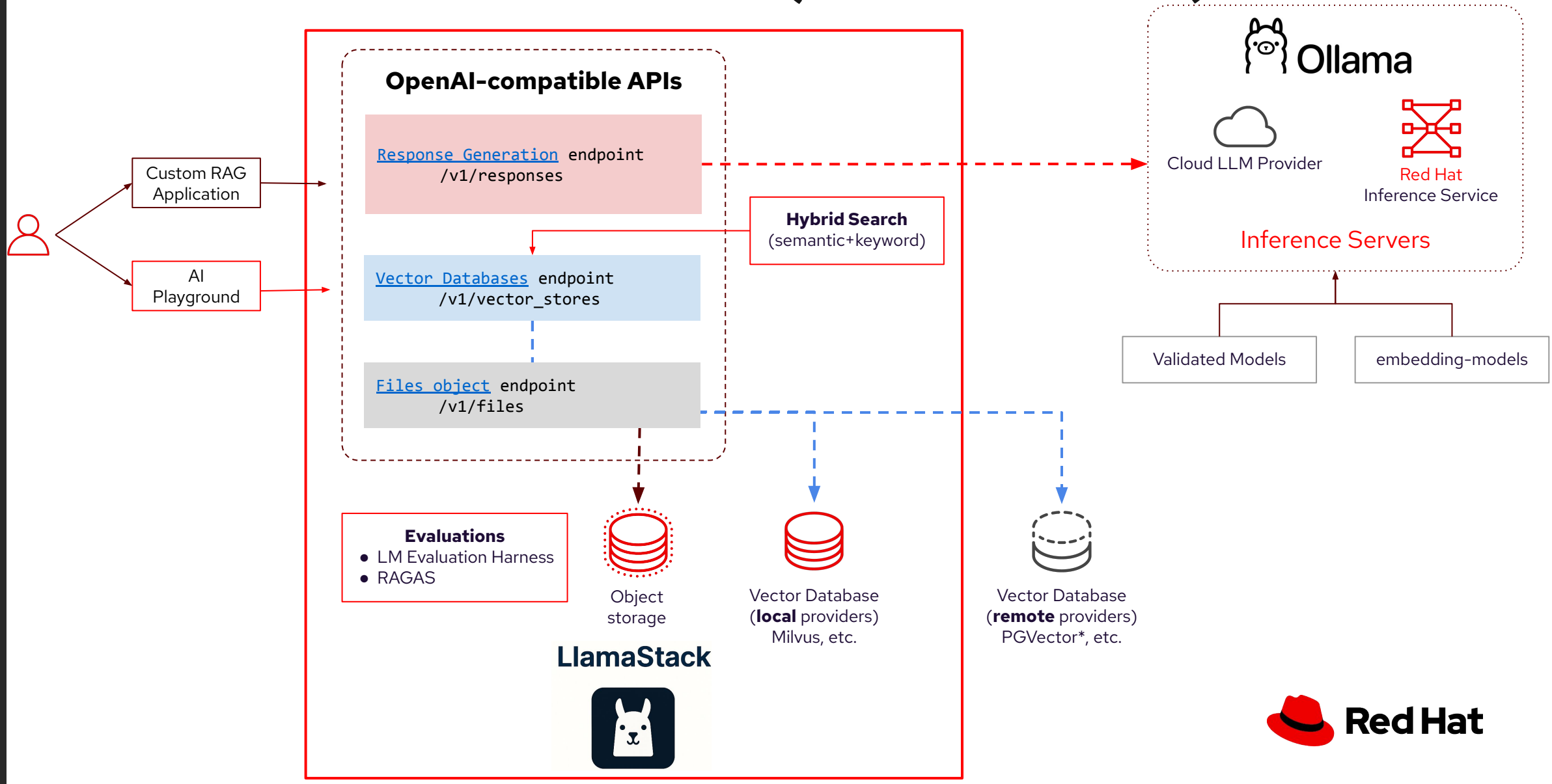
- Central API Server manages the AI flow
- Modular components: Inference, Retrieval, Memory, Tools, Guardrails, Telemetry
- Mix, match, replace…
- Compatible with Ollama, vLLM, Milvus, pgvector, etc.
- Designed for portability and compliance
- **Standardized APIs, interoperable protocols, and pluggable providers**



Main Building Blocks

- **VectorStore**: perform operations on vector DBs, such as adding documents, searching, and deleting documents
- **Tooling**: integrate with tools using MCP protocol
- **Safety**: apply safety policies (including Guardrails) to the output at a Systems (not only model) level
- **Inference** (Responses API): run inference with a LLM and multi-step agentic workflows with LLMs with tool usage, memory (RAG), etc.
- **Eval**: generate outputs (via Inference or Agents) and perform scoring
- **Telemetry**: collect telemetry data from the system

RAG with Llama Stack (End-to-End)



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RAG Demo !

Red Bank Financial

Use Case – Red Bank Financial

Our use case is a customer service scenario for Red Bank Financial

- **Pain points:**
  - **Long queue times.**
  - **Callers must listen to every menu option before selecting the right one.**
  - **Limited 24/7 availability.**
  - **Long resolution times.**

Use Case – Red Bank Financial

Our use case is a customer service scenario for Red Bank Financial

If we ask an LLM about Red Bank Financial:

It will have no knowledge.

What if...

We provide documents from Red Bank Financial with company information.

With RAG:

The model can now answer accurately to requests.

Example: “What is Red Bank Financial?” → reliable answer.

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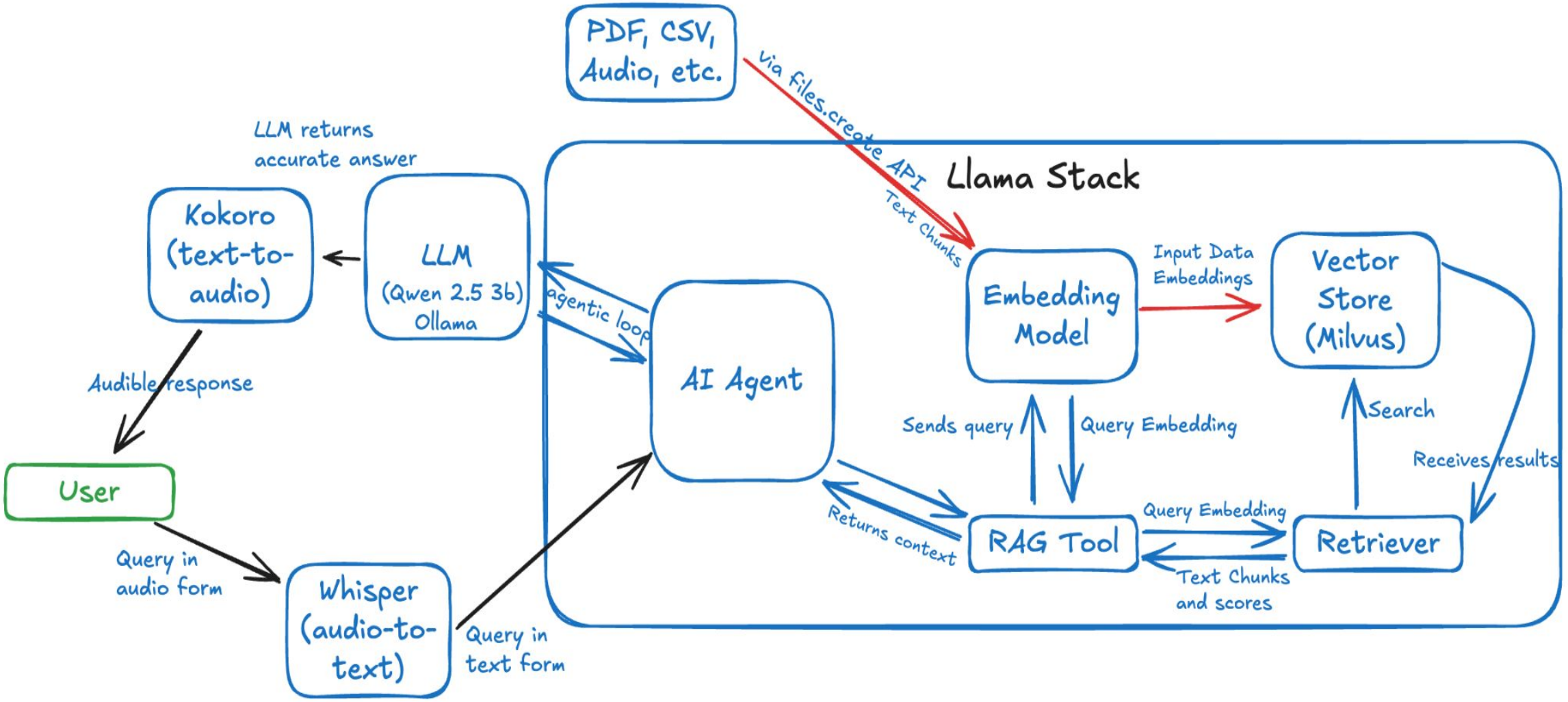
LlamaStack

Solution Architecture



Demo on YouTube:

https://youtu.be/GYtG8ic7XJ4