



WELCOME

How MongoDB and Voyage AI Build Your Agentic System



Ainara Miller-Askar
Solutions Architect

Hello from a full-time working parent



Bring to school

WORK

Pick up from school

Order bigger shoes

Order books &
development stuff

Quality time
with my
daughter

WORK

Clean up home

WORK

Cook dinner

Order bigger outfit
for the dance contest

WORK

Schedule pediatrician

Do groceries

1:1 with teachers
at school

Quality time
with my
partner

WORK

Plan school holidays

Good-night story

Rest of the family?
Friends?

ME TIME???



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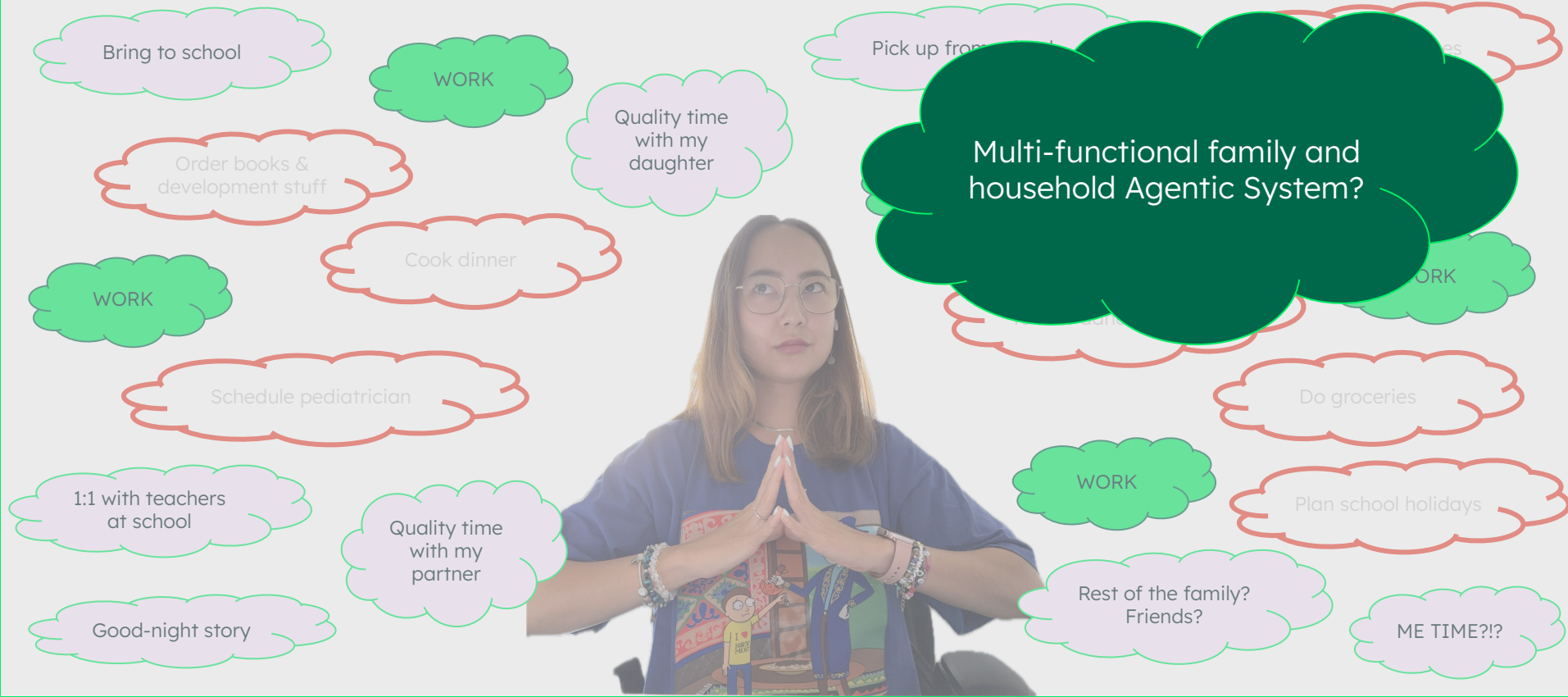
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Hello from a full-time working parent





Hello from a full-time working parent





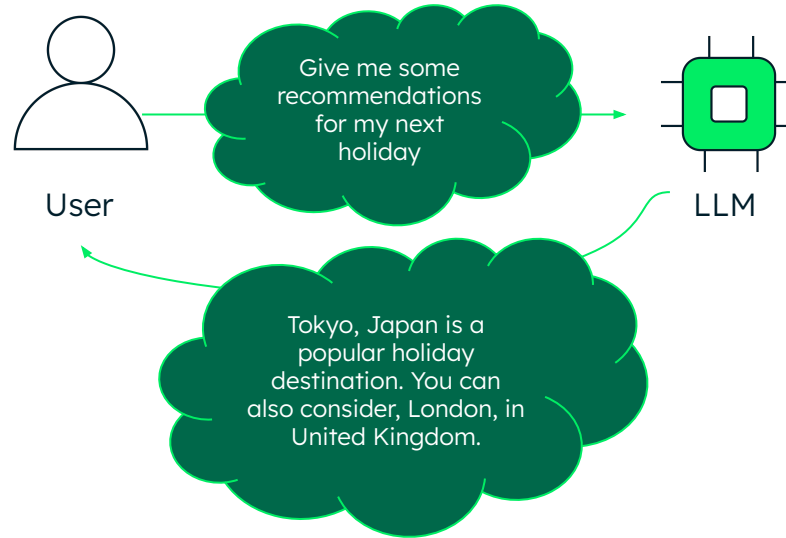
Form Factor Evolution



LLM Powered Chatbots

Knowledge in models used
to respond to queries

Traditional Chatbots to LLM Powered Chatbots





Form Factor Evolution



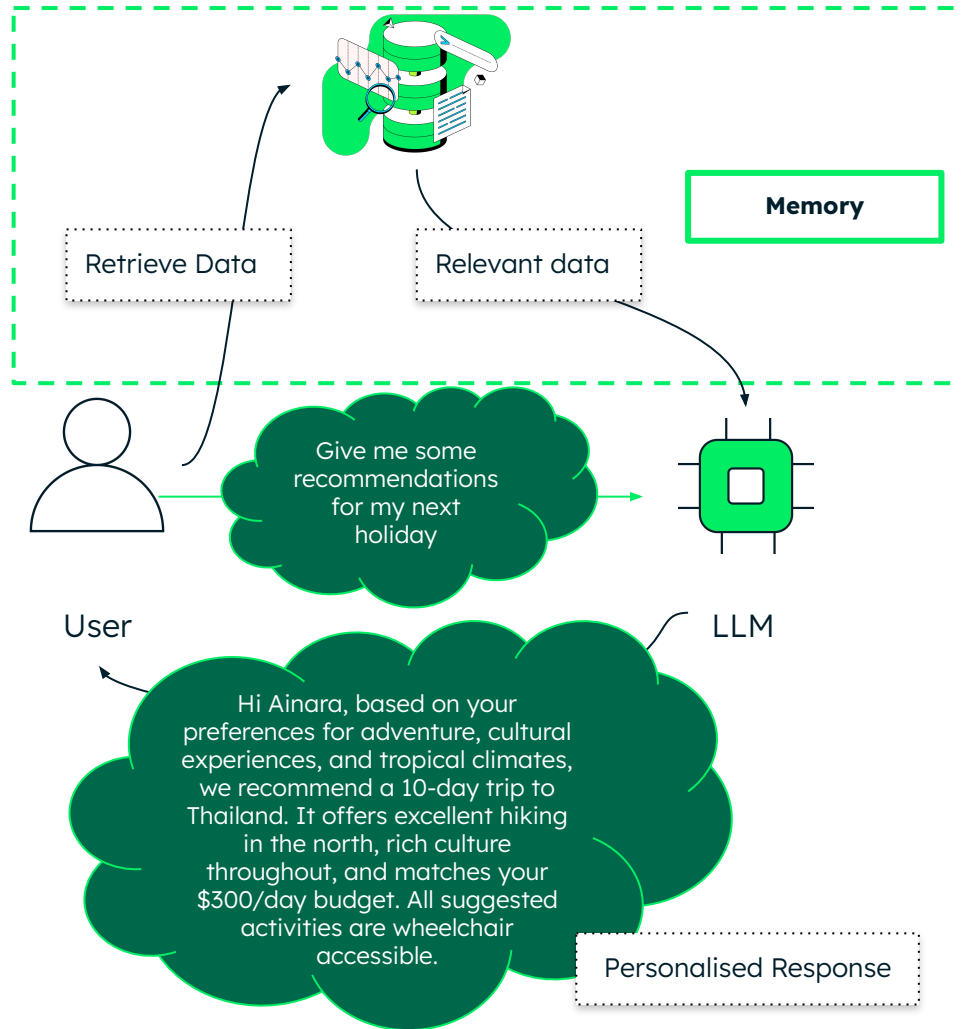
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Knowledge in models used
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RAG Chatbots

Knowledge in models
supplemented with
external data

LLM Powered Chatbots to RAG Chatbots



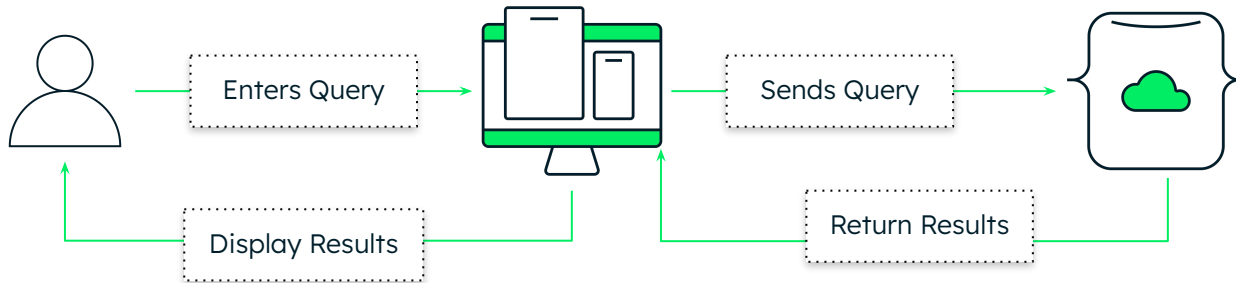
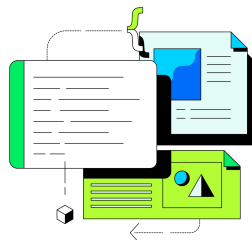


Challenges

Provide the right information to LLM

\$search

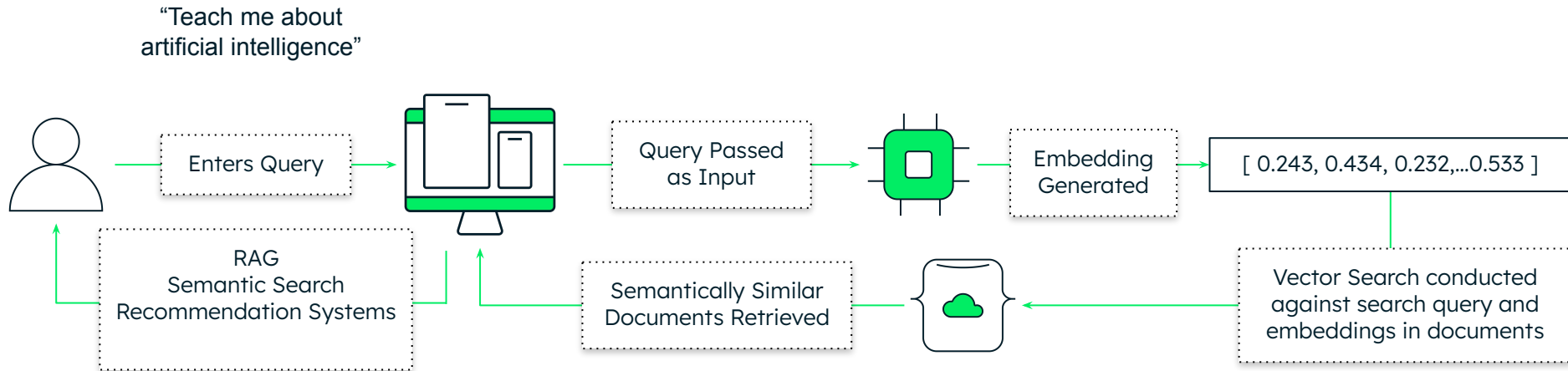
“artificial intelligence”



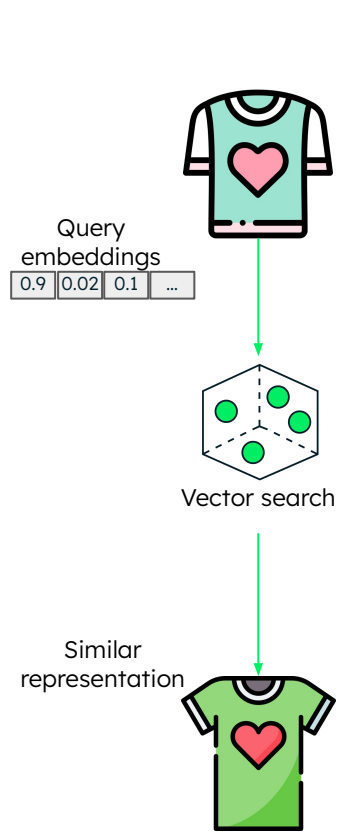
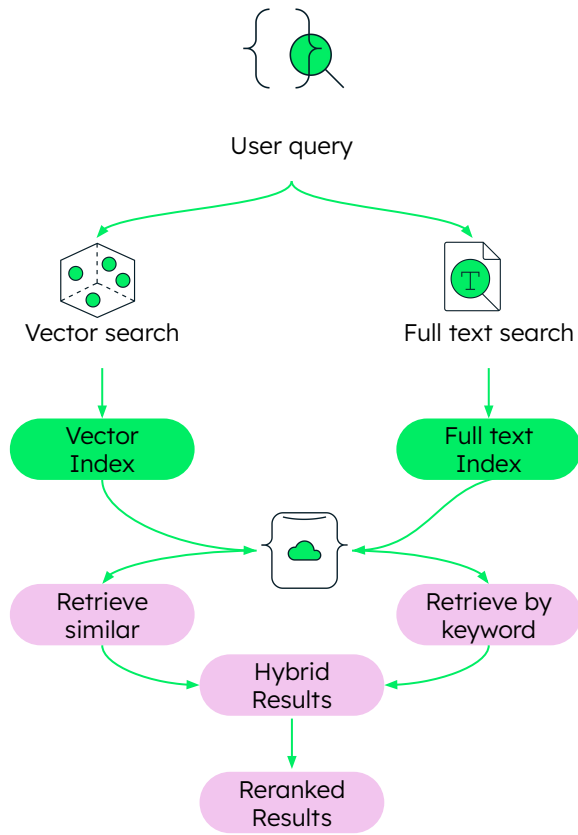
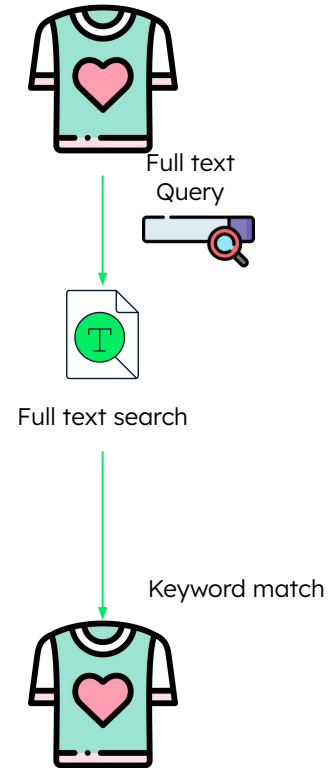
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```

MongoDB Atlas Vector Search

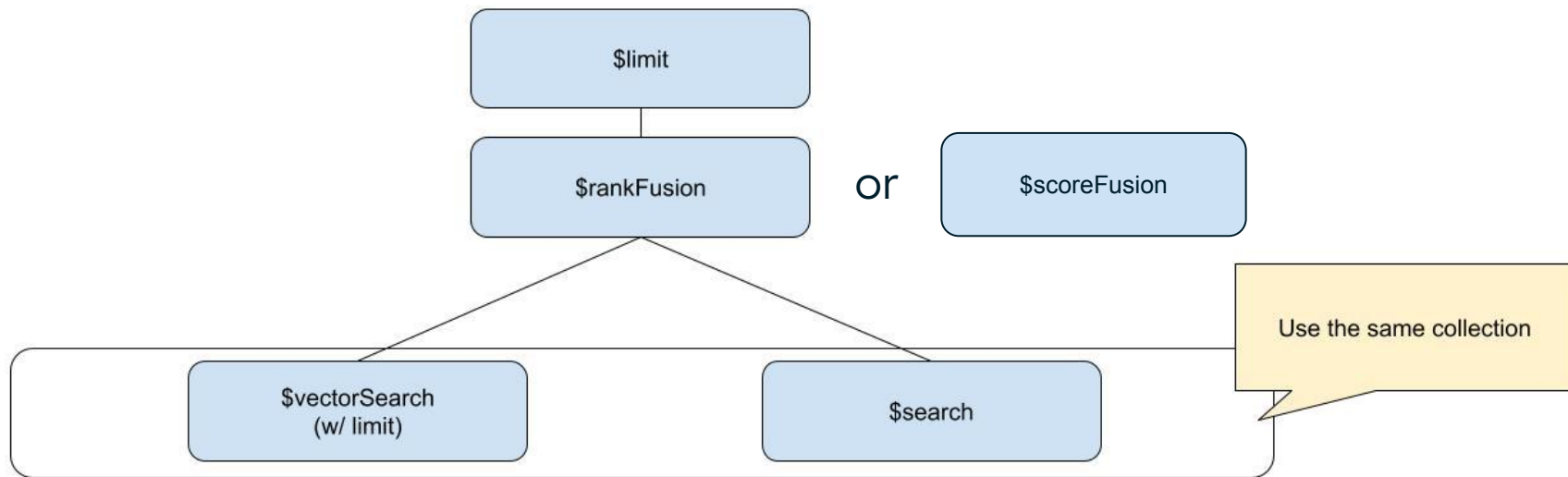
\$vectorSearch



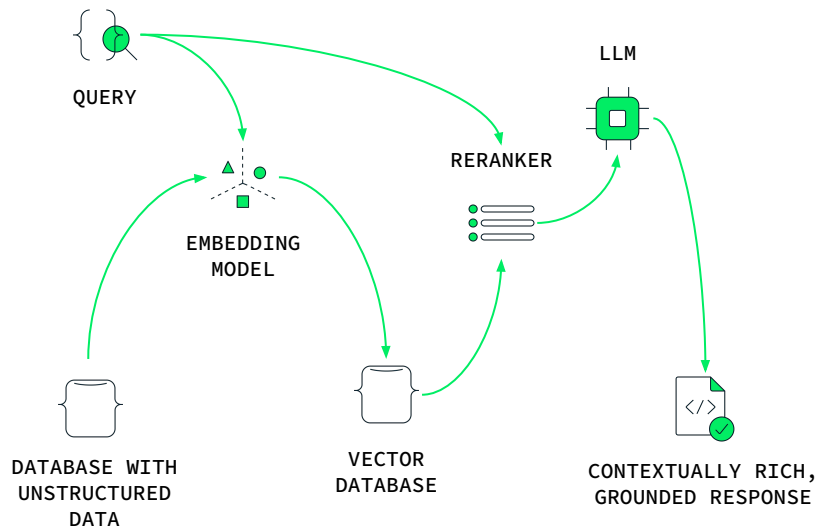
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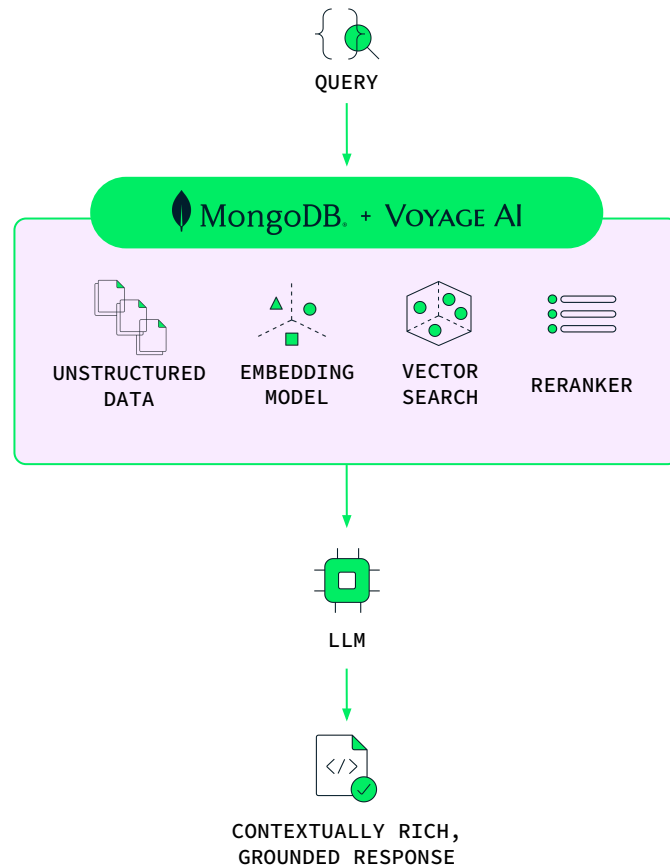
Hybrid Search via \$rankFusion or \$scoreFusion



BEFORE

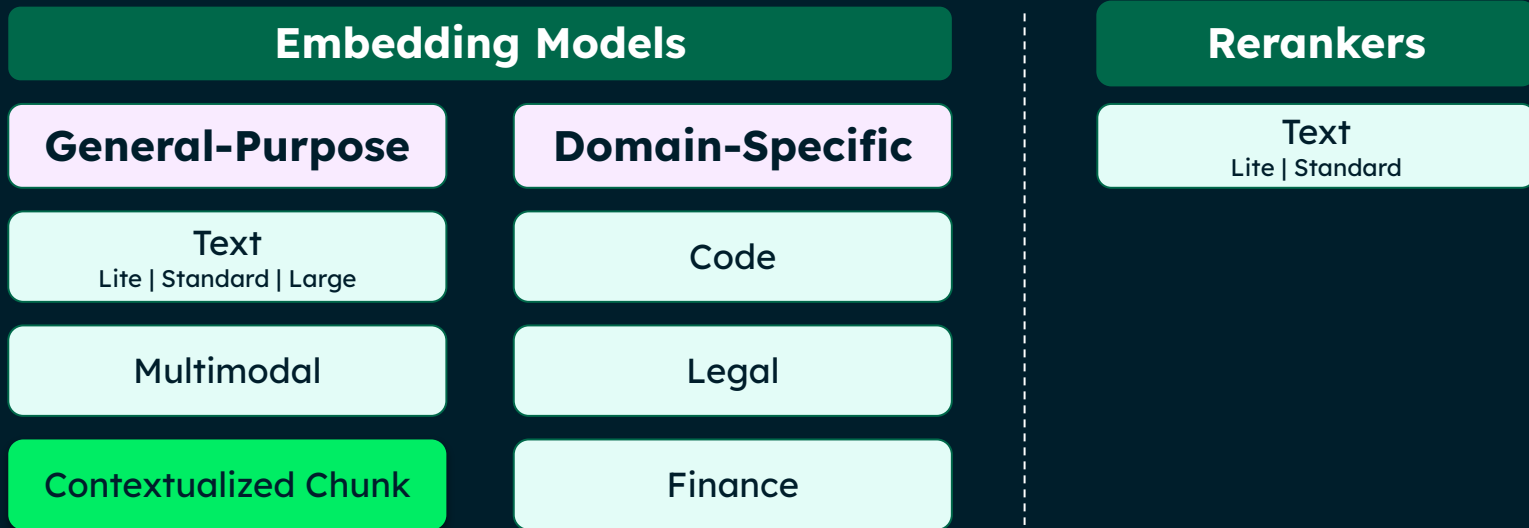


AFTER





Expanding Voyage AI's model offering with contextualized chunk embeddings

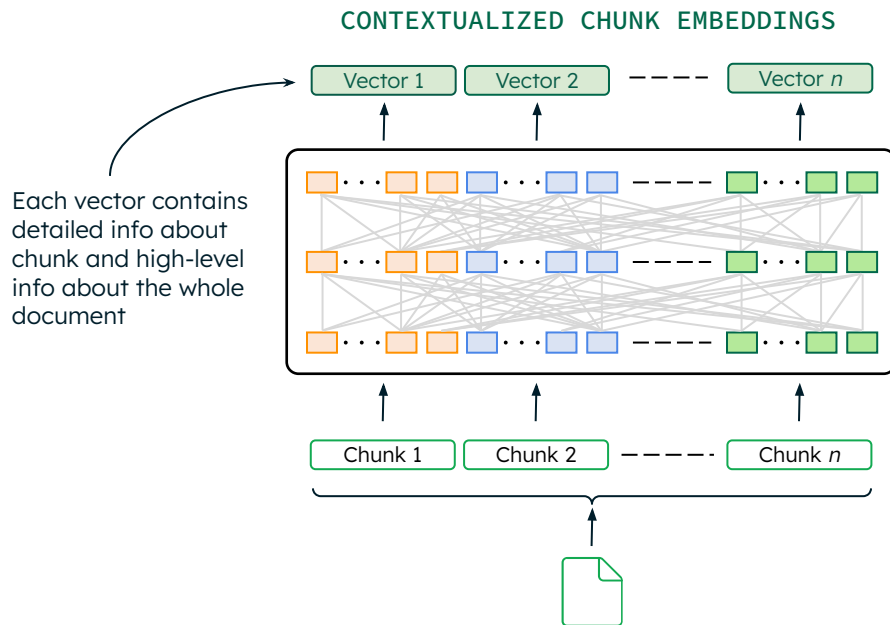




voyage-context-3

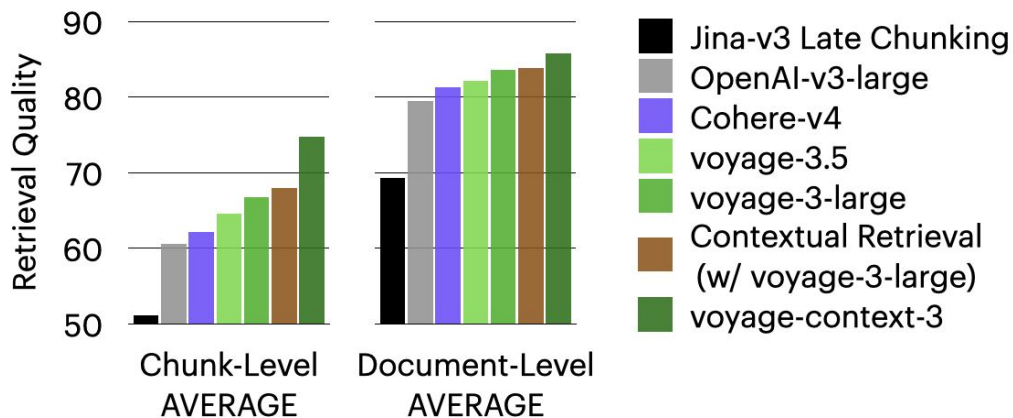


voyage-context-3: A breakthrough in precise chunk retrieval with global document context



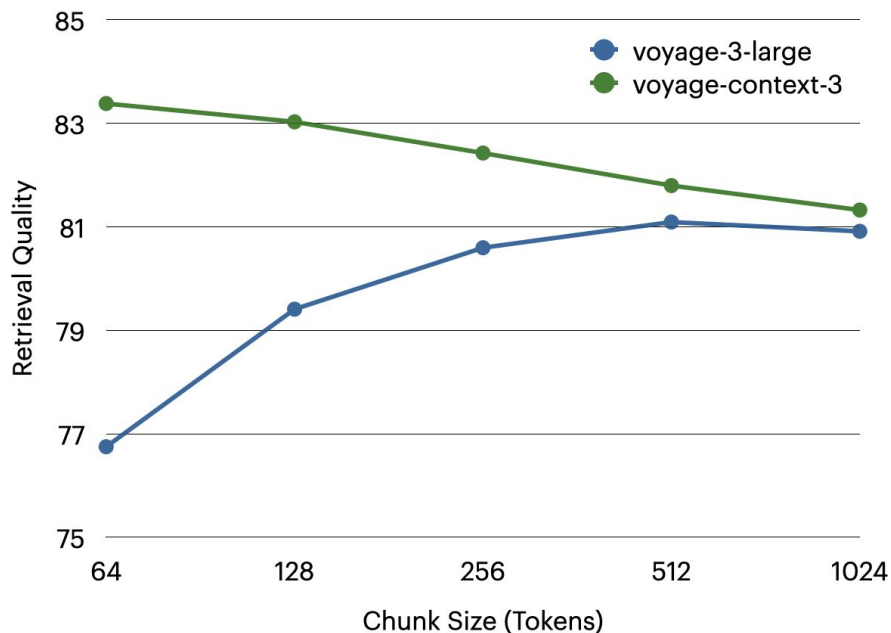


Contextualized chunk embeddings deliver superior retrieval performance





Reduced sensitivity to chunking size



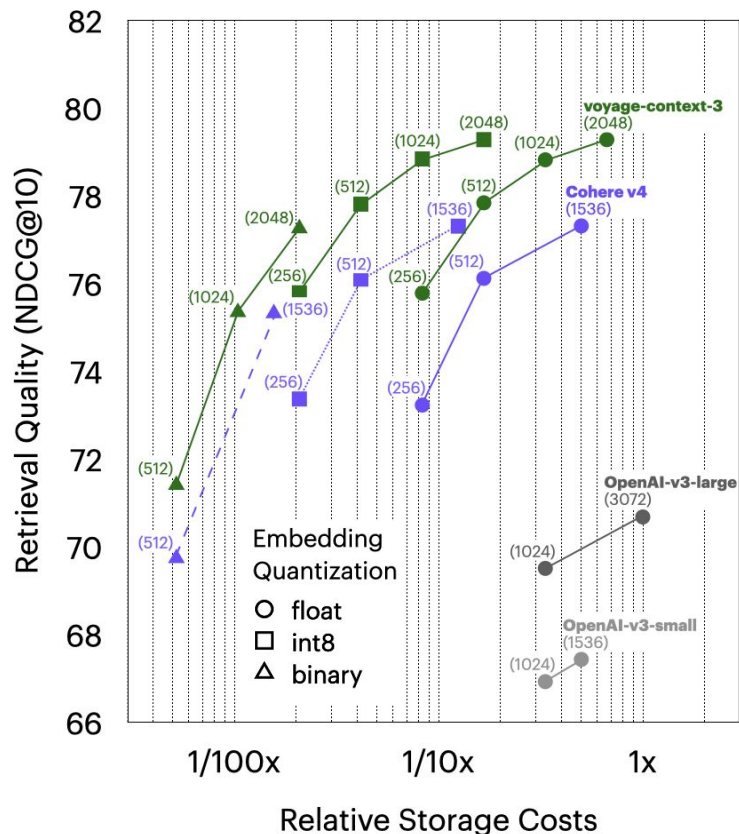


Minimizing quality loss across quantization options

Compared to OpenAI-v3-large (float, 3072),
voyage-context-3:

- int8 with 2048 dims: **reduces vector db costs by 83%** with **8.60%** better retrieval quality.
- binary with 512 dims: reduces vector db costs by 99.48% with 0.73% better retrieval quality—that's virtually the **same retrieval performance at 0.5% of the cost.**

voyage-context-3



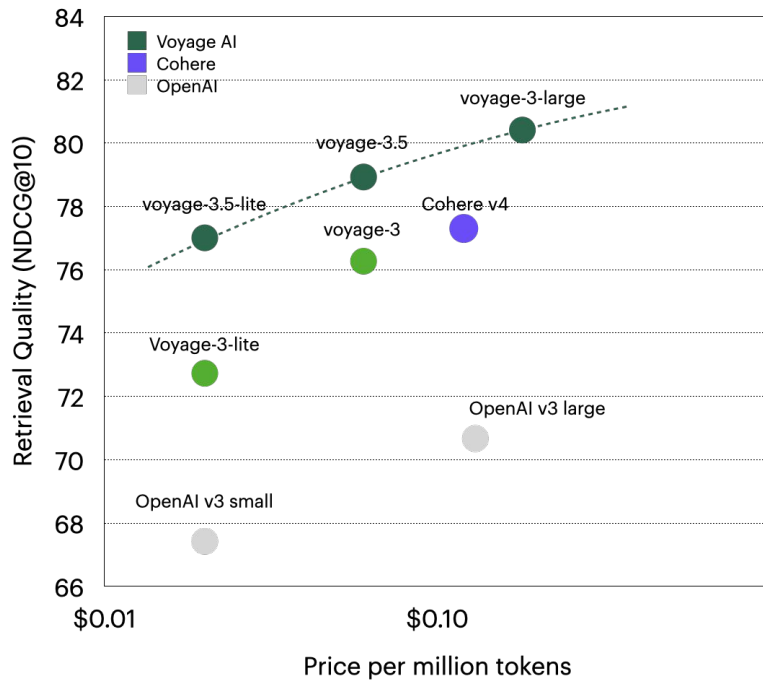


voyage-3.5 and
voyage-3.5-lite



voyage-3.5 and voyage-3.5-lite

New frontier for price-performance





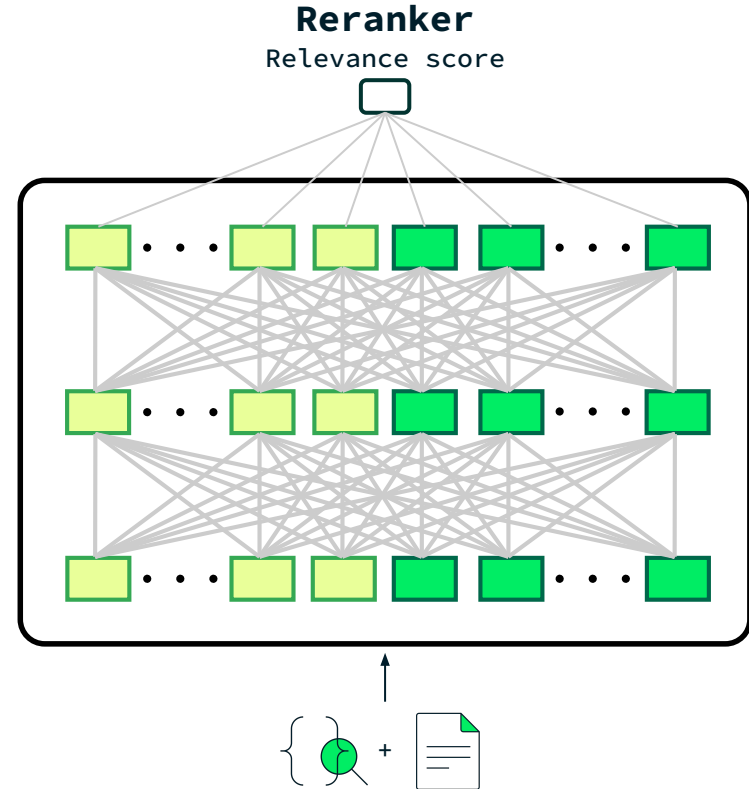
rerank-2.5 & 2.5-lite



What are rerankers and how do they work?

Rerankers (or reranking models) are cross-encoder models that assign relevance scores to a query and retrieved documents.

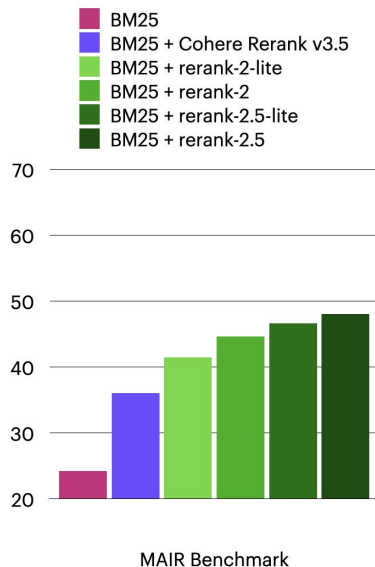
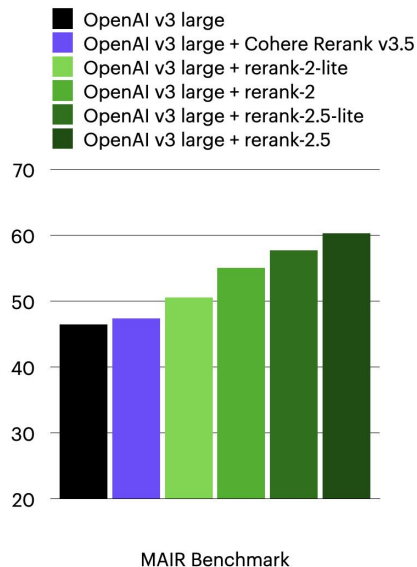
Given a query and a set of documents, rerankers return a rank for each document per its relevance to the query. This process can help improve the relevance of semantic search results.



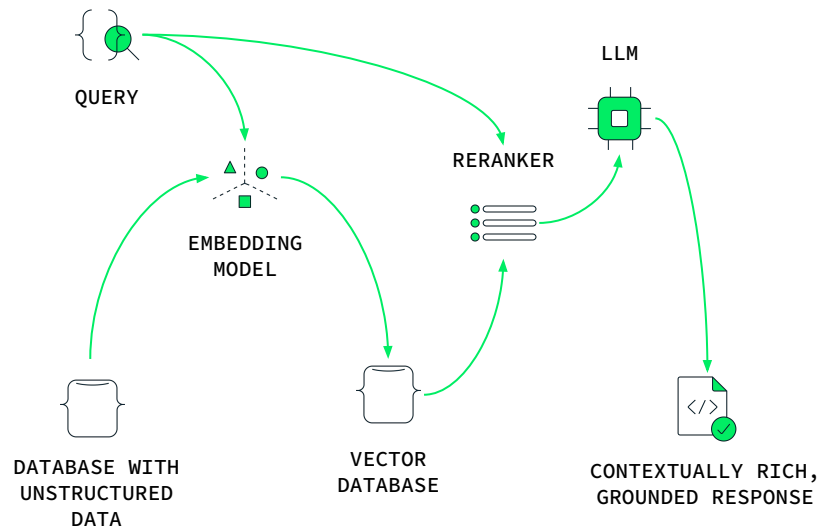


MAIR benchmark performance

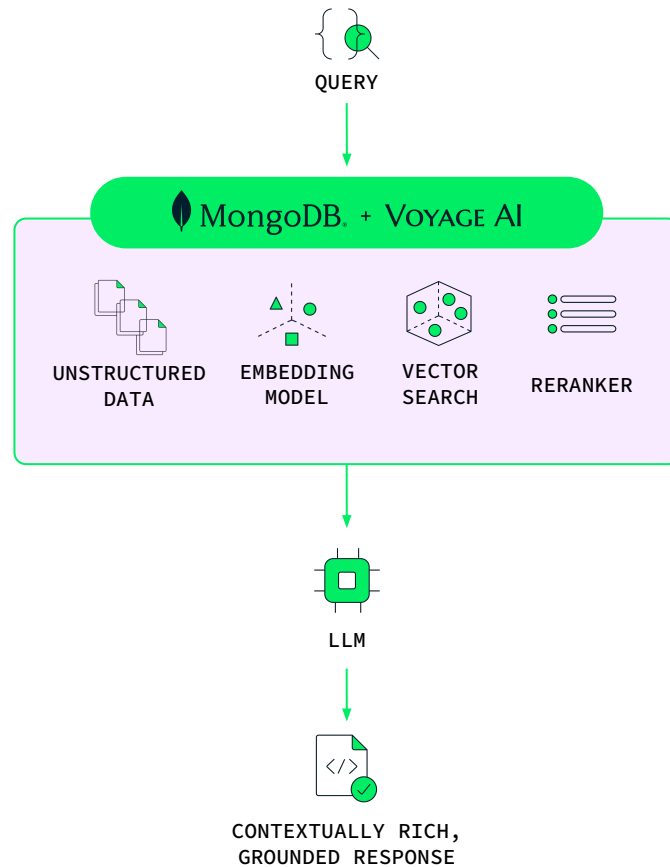
rerank-2.5 and rerank-2.5-lite outperform competitors



BEFORE

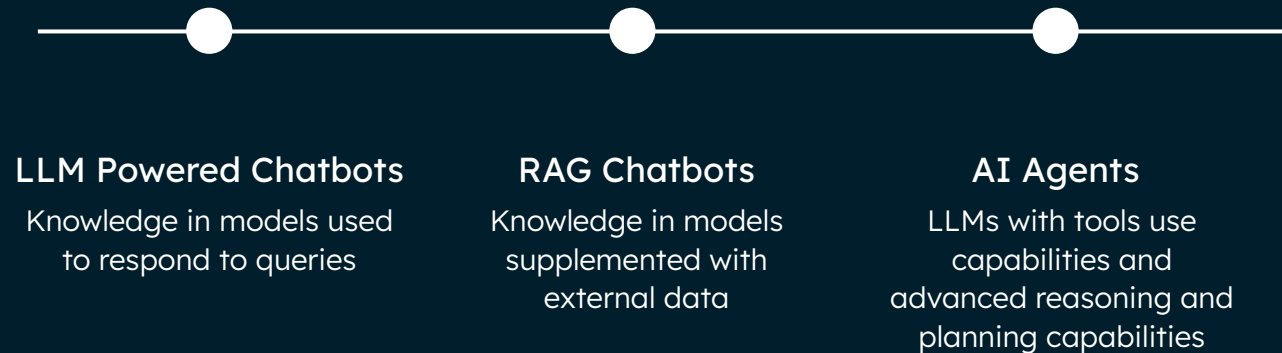


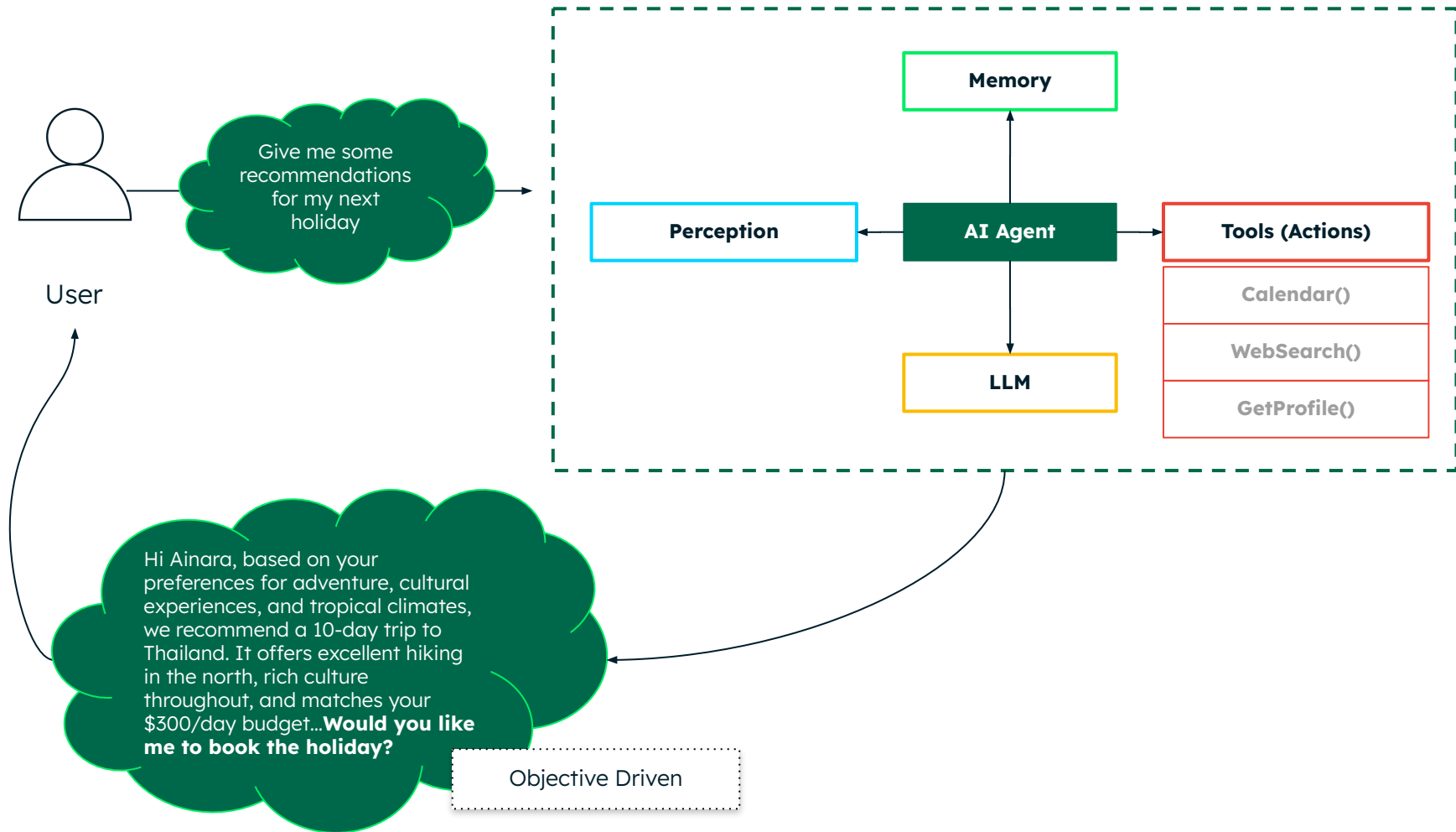
AFTER





Form Factor Evolution







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RAG Chatbots

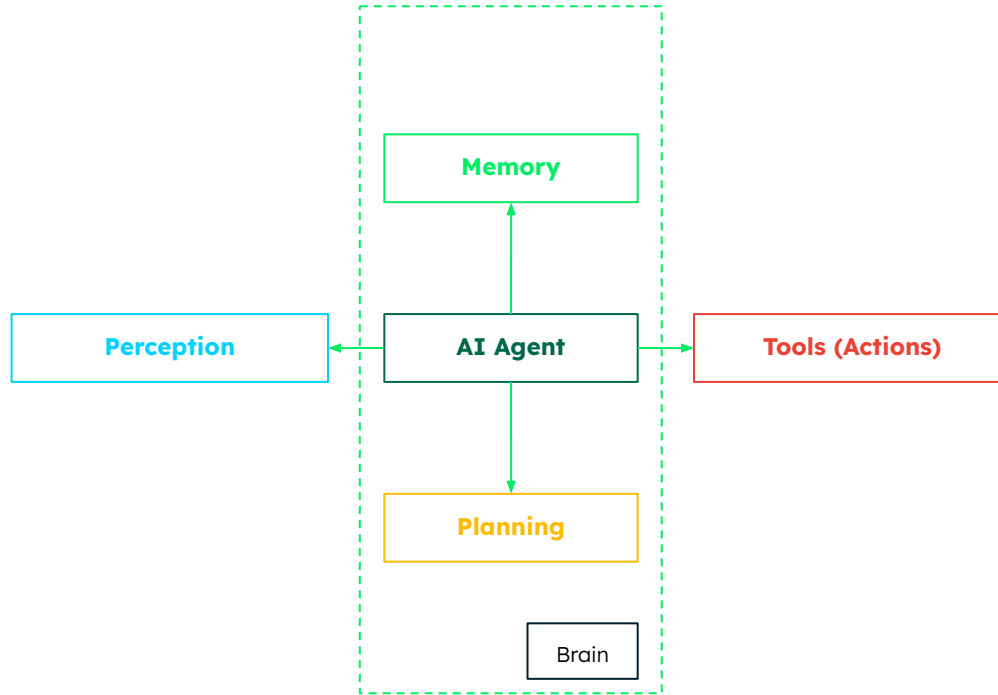
Knowledge in models
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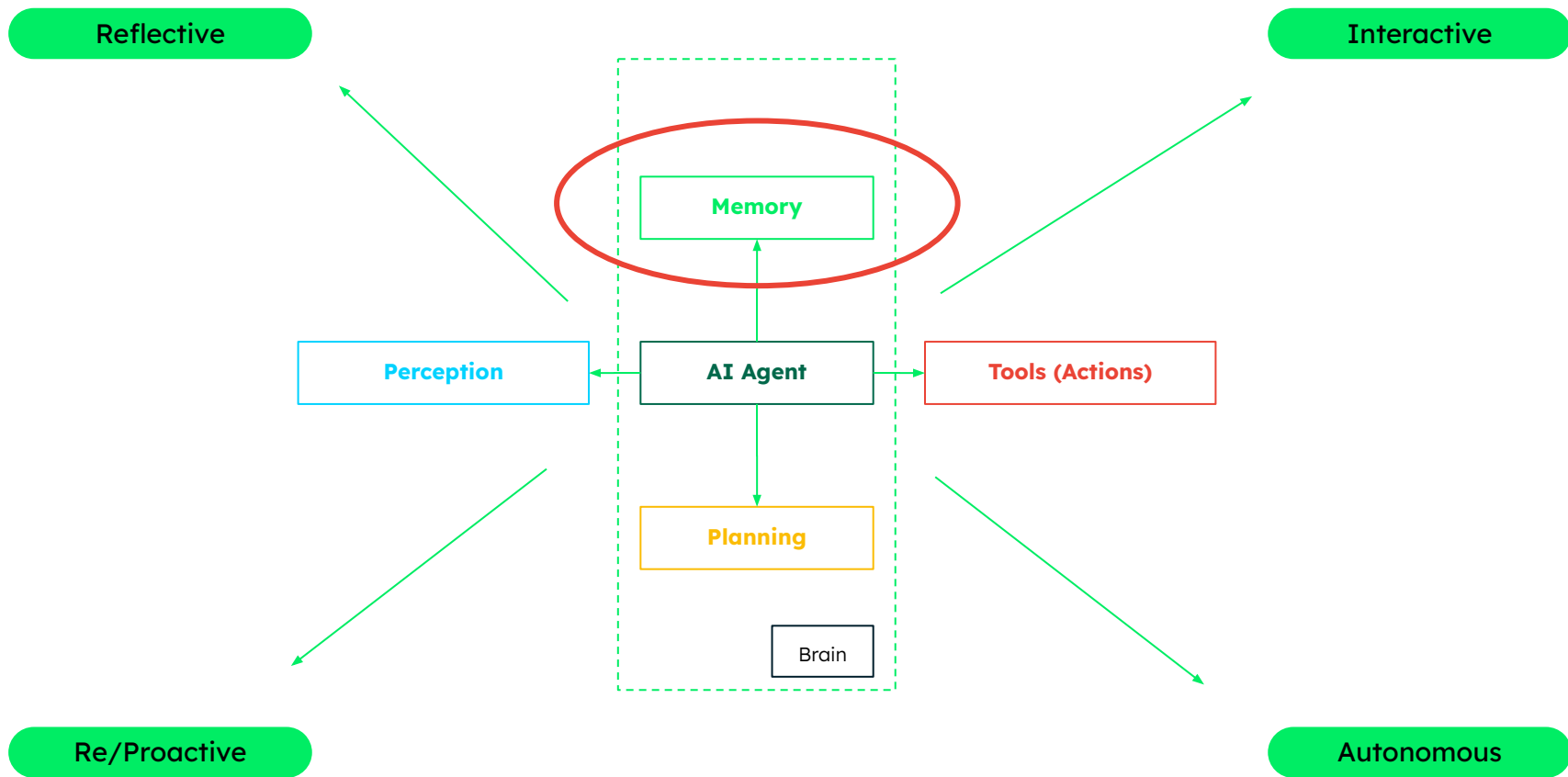
AI Agents

LLMs with tools use
capabilities and
advanced reasoning and
planning capabilities

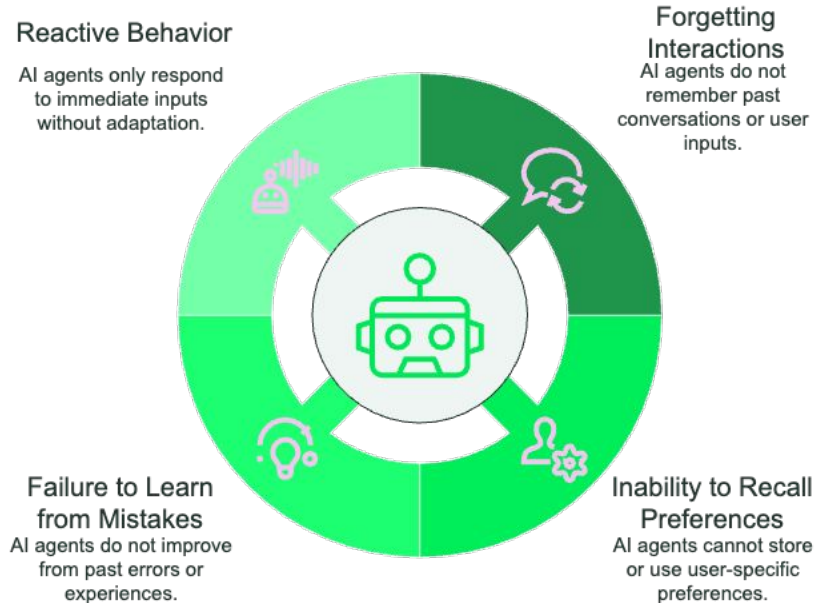
Agentic Systems

System architecture
consisting of multiple tools,
AI agents, and components





Why Building Truly Intelligent Agents Is So Hard?



Modern AI agents may seem smart, but most are stateless.

The result?

- Repetitive conversations
- High token and compute costs
- No long-term personalization

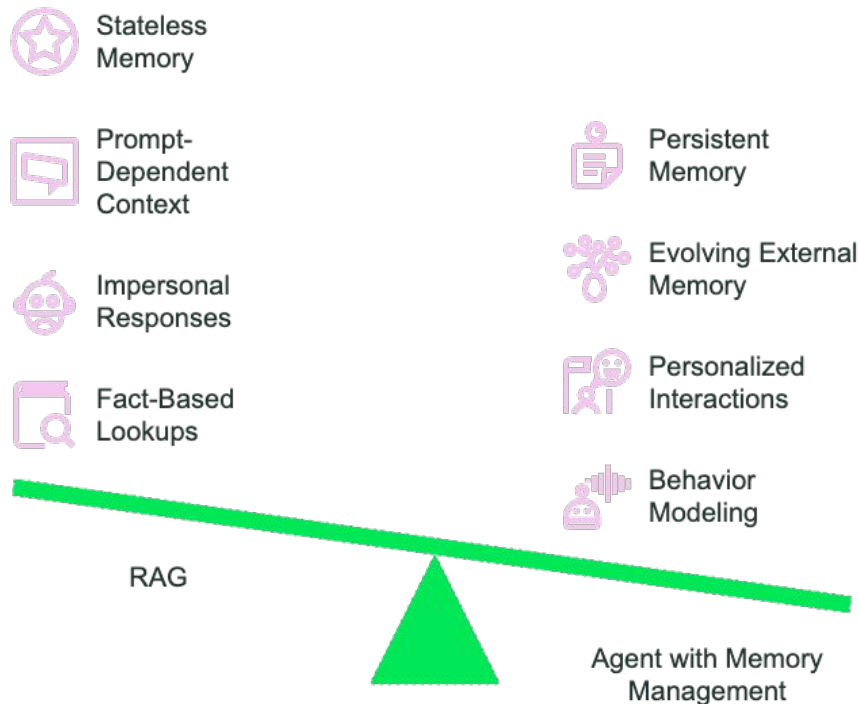
MongoDB Memory + RAG: Complementary Power

RAG (Retrieval-Augmented Generation) is excellent for fetching knowledge from documents, but it is **stateless**.

It lacks memory of **who** the user is, **what** they asked, or **why** something failed last time.

MongoDB Memory solution bridges that gap by enabling:

- **Continuity** across sessions
- **Personalized decision-making**
- **Behavioral memory**, not just factual recall





MongoDB Memory for AI agents

Memory Types

Short Term

Procedural

Long Term

Taxonomic

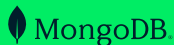
Agentic Frameworks

LangGraph

CrewAI

AutoGen

Custom / Others



OLTP



VECTOR
SEARCH



FULL-TEXT
SEARCH



ANALYTICS



STREAM
PROCESSING



TIME
SERIES

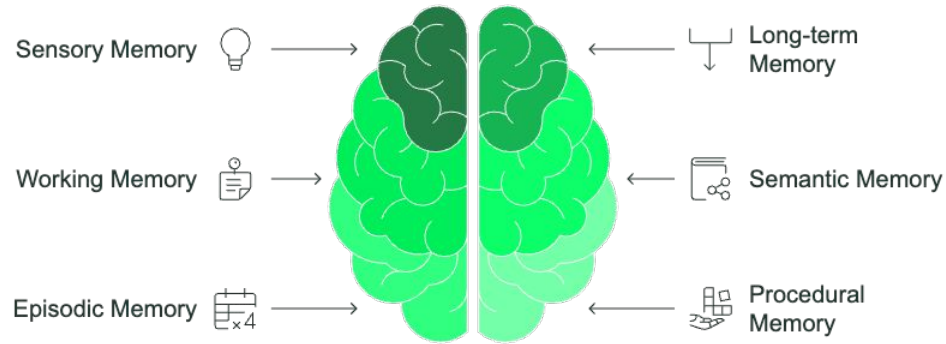


EMBEDDING
MODELS

Multi-Cloud Scale, Resilience, Performance, & Security

supporting short-term and long-term memory, and state persistence on multimodal data

Human Memory

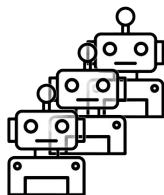


The most effective form of intelligence -
for now - is human intelligence, and
human memory capabilities
substantially define intelligence.

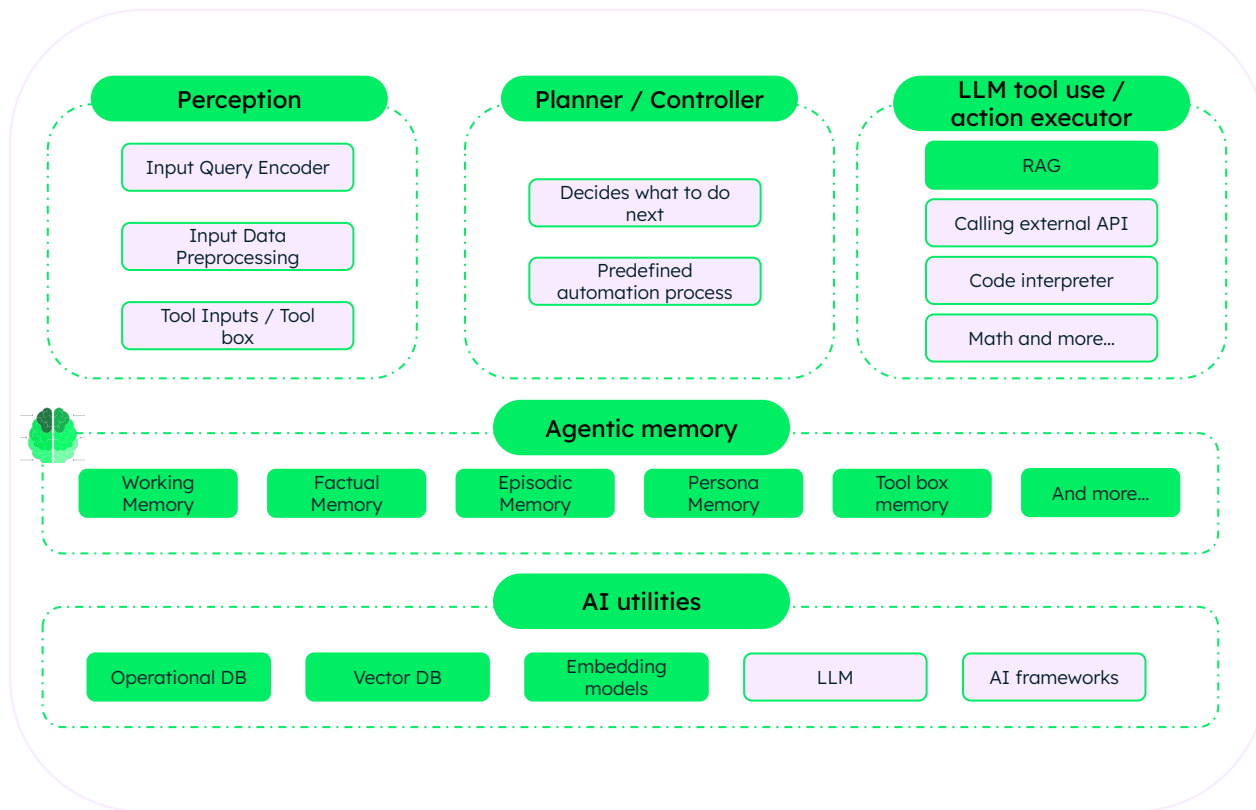
How does MongoDB memory solution fit?



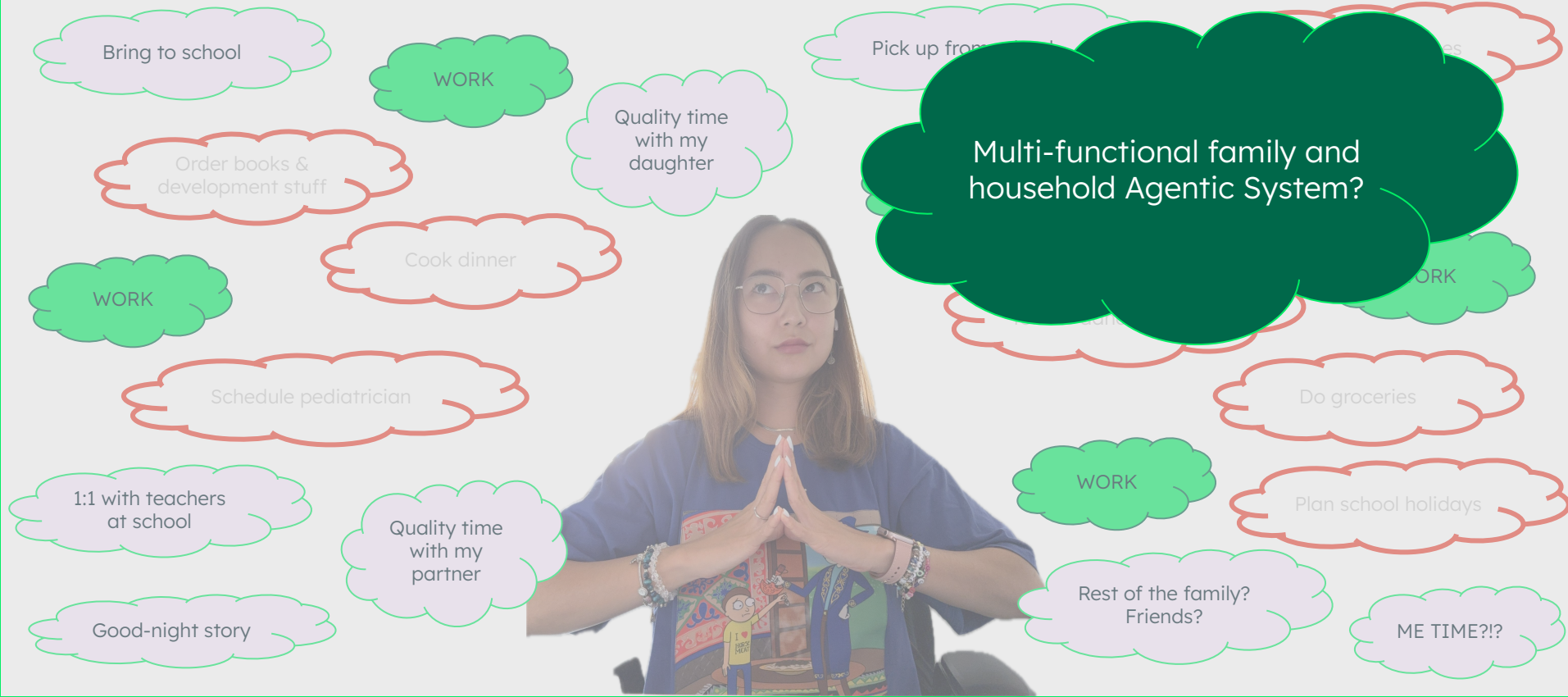
User



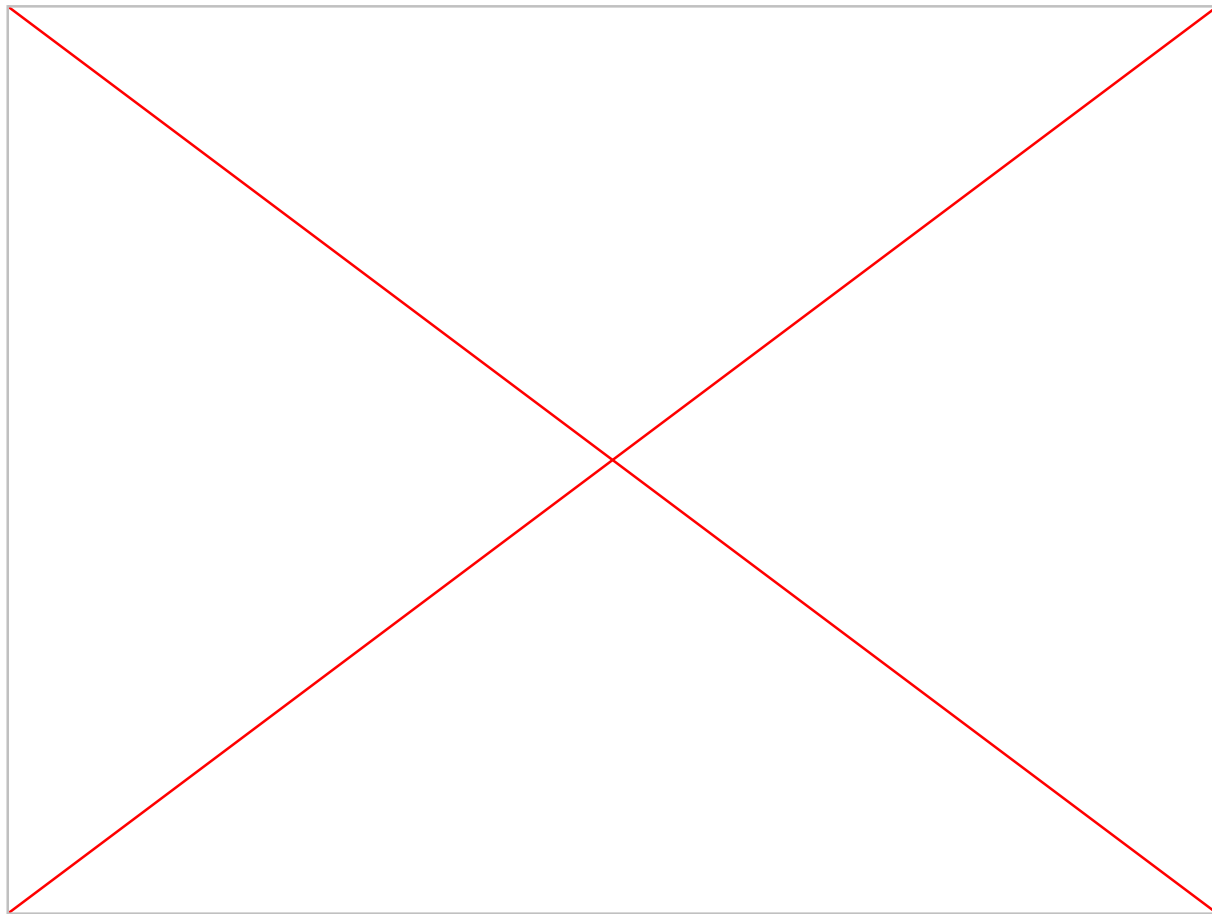
Agentic system



Hello from a full-time working parent



Demo





MongoDB as Agentic Memory

The screenshot shows the MongoDB Atlas Data Explorer interface. The left sidebar contains navigation options: Overview, DATABASE, Clusters, Data Explorer, SERVICES, Atlas Search, Stream Processing, Triggers, Migration, Data Federation, SECURITY, Backup, Database Access, Network Access, and Advanced. The main panel displays the 'amazon_products' collection. A search bar is at the top, and a 'Type a query: (field: 'value') or [Generate Query](#)' prompt is below it. Below the search bar are buttons for 'ADD DATA', 'UPDATE', and 'DELETE'. The collection is expanded, showing a list of documents. The first document is highlighted, showing fields like '_id', 'product_id', 'name', 'category', 'subcategory', 'age_range', 'rating', 'price', 'author', 'description', 'amazon_url', and 'image_url'. The bottom of the screen shows the system status: 'System Status: All Good' and '©2025 MongoDB, Inc. Status Terms Privacy Atlas Blog Contact Sales'.

The screenshot shows the MongoDB Atlas Data Explorer interface. The left sidebar contains navigation options: Overview, DATABASE, Clusters, Data Explorer, SERVICES, Atlas Search, Stream Processing, Triggers, Migration, Data Federation, SECURITY, Backup, Database Access, Network Access, and Advanced. The main panel displays the 'pantry_inventory' collection. A search bar is at the top, and a 'Type a query: (field: 'value') or [Generate Query](#)' prompt is below it. Below the search bar are buttons for 'ADD DATA', 'UPDATE', and 'DELETE'. The collection is expanded, showing a list of documents. The first document is highlighted, showing fields like '_id', 'product_id', 'name', 'category', 'subcategory', 'age_range', 'rating', 'price', 'author', 'description', 'amazon_url', and 'image_url'. The bottom of the screen shows the system status: 'System Status: All Good' and '©2025 MongoDB, Inc. Status Terms Privacy Atlas Blog Contact Sales'.

\$vectorSearch and custom rerank?



```
def get_voyage_embedding(self, plot, model='voyage-3-large'):
    response = self.voyage_client.embed([plot], model=model, input_type="document").embeddings
    return response[0]
```

```
# Search recipes using MongoDB $vectorSearch
if self.mongo.voyage_client:
    query_embedding = self.mongo.get_voyage_embedding(query)

    # Use MongoDB aggregation pipeline with $vectorSearch
    pipeline = [
        {
            "$vectorSearch": {
                "index": "vector_search_index",
                "path": "embedding",
                "queryVector": query_embedding,
                "numCandidates": 20,
                "limit": 10
            }
        },
        {
            "$addFields": {
                "vector_score": {"$meta": "vectorSearchScore"}
            }
        }
    ]

    # Execute aggregation pipeline
    recipes = list(self.mongo.recipe_database.aggregate(pipeline))
```

```
# Get pantry items
pantry = self.mongo.pantry_inventory.find_one({"user_id": user_id})
pantry_items = [item["name"] for item in pantry.get("items", [])] if pantry else []

# Get family preferences
preferences = self.mongo.family_preferences.find_one({"user_id": user_id})
preferred_cuisines = preferences.get("preferred_cuisines", []) if preferences else []
health_goals = preferences.get("health_goals", []) if preferences else []
```

```
# Score recipes based on additional factors
scored_recipes = []
for recipe in recipes:
    recipe_ingredients = [ing["name"] for ing in recipe.get("ingredients", [])]

    # Get vector score from MongoDB
    vector_score = recipe.get("vector_score", 0)

    # Calculate pantry match score (capped to prevent domination)
    pantry_matches = len(set(recipe_ingredients) & set(pantry_items))
    pantry_score = min(pantry_matches / len(recipe_ingredients), 0.7) if recipe_ingredients else 0

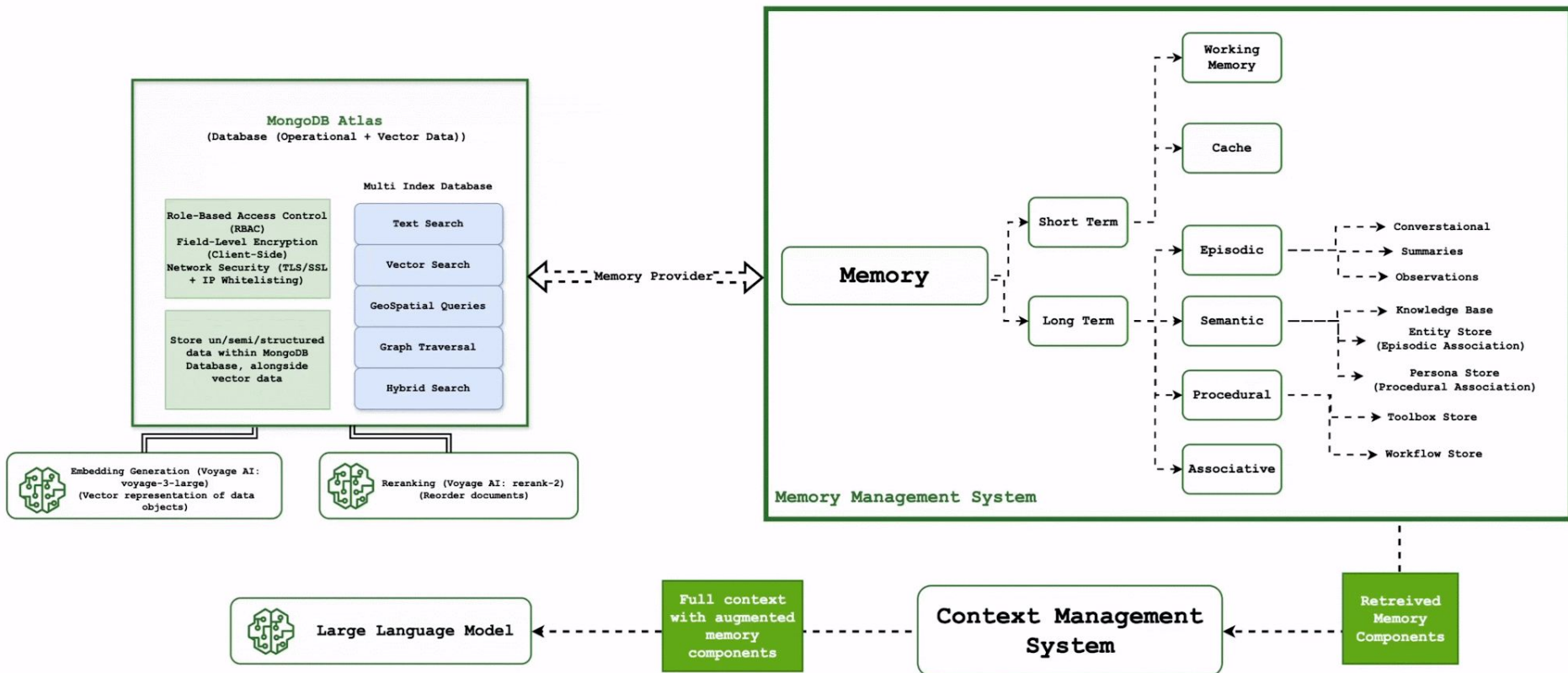
    # Calculate cuisine preference score
    cuisine_score = 0
    for cuisine in preferred_cuisines:
        if cuisine in recipe.get("tags", []):
            cuisine_score += 0.3

    # Calculate health goal score
    health_score = 0
    for goal in health_goals:
        if goal in recipe.get("tags", []):
            health_score += 0.2

    # Overall score with vector similarity (prioritize semantic matching)
    total_score = (vector_score * 0.9) + (pantry_score * 0.05) + (cuisine_score * 0.03) + (health_score * 0.02)

    scored_recipes.append({
        "recipe_id": recipe["recipe_id"],
        "name": recipe["name"],
        "cooking_time": recipe["cooking_time"],
        "health_score": recipe["health_score"],
        "difficulty": recipe["difficulty"],
        "pantry_matches": pantry_matches,
        "total_ingredients": len(recipe_ingredients),
        "missing_ingredients": list(set(recipe_ingredients) - set(pantry_items)),
        "available_ingredients": list(set(recipe_ingredients) & set(pantry_items)),
        "total_score": total_score,
        "tags": recipe.get("tags", [])
    })

# Sort by total score
scored_recipes.sort(key=lambda x: x["total_score"], reverse=True)
```





Let's connect!



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