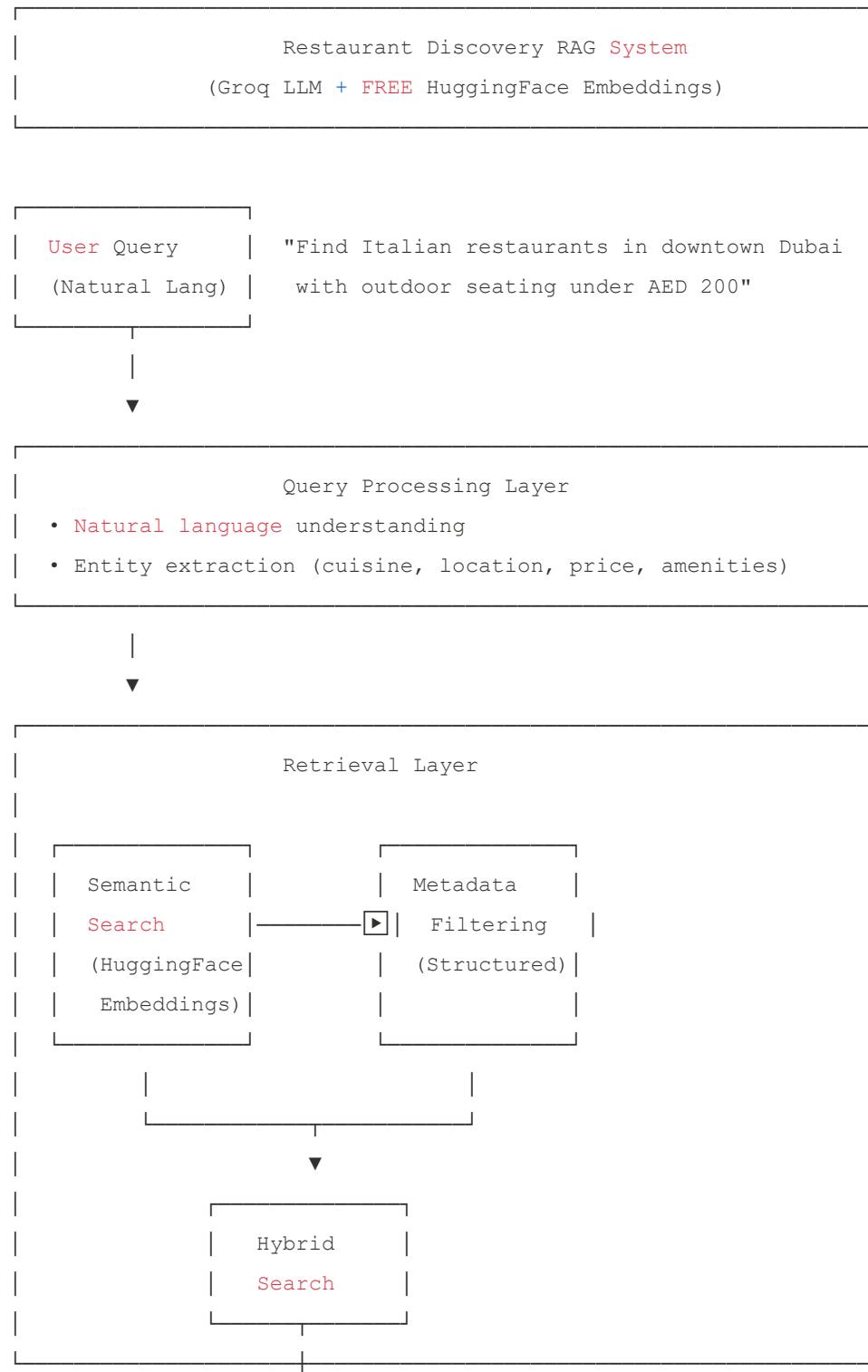


RAG System Architecture (Task 1.1)

1. System Overview

This document outlines the production-ready Retrieval-Augmented Generation (RAG) architecture designed for the Restaurant Discovery System. It leverages a cost-optimized, high-performance stack combining **Groq** for inference and **HuggingFace** for local embeddings.

2. Architecture Diagram



Vector Database (ChromaDB)

Restaurant Documents (50 restaurants)

- Text: Name, cuisine, location, description, amenities
- Metadata: ID, price_range, rating, coordinates
- Embeddings: HuggingFace [all-MiniLM-L6-v2](#) (**FREE!**)

Embedding Model: HuggingFace [all-MiniLM-L6-v2](#)

- Dimension: [384](#)
- **FREE** – No API key needed!
- Runs locally [on CPU](#)

Generation Layer (Groq LLM)

LLM: Groq ([llama-3.1-8b-instant](#))

- Context: Retrieved restaurant documents
- Prompt: Custom template [for](#) restaurant recommendations
- Output: [Natural language response with matches](#)
- Speed: [10x faster than OpenAI](#)

Contextual Response (Natural Lang)	"Based on your criteria, I found 3 Italian restaurants in Downtown Dubai with outdoor seating under AED 200: [restaurant details]"
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3. Technology Stack & Rationale

Component	Choice	Rationale
Orchestration	LangChain 1.0	Industry standard for RAG; provides robust chains, retrievers, and LCEL (LangChain Expression Language) for modern composition.
Vector DB	ChromaDB	Lightweight and embedded. It requires no separate server, supports persistent storage, and offers efficient similarity search for the dataset size.
Embeddings	HuggingFace (sentence-transformers)	100% Free & Local. Runs on CPU without API keys. Provides 384-dimensional vectors that balance quality with speed.
LLM	Groq (llama-3.1-8b)	Speed. Inference is ~10x faster than OpenAI, which is critical for real-time search. The free tier is generous for development.

4. Data Pipeline Implementation

Step 1: Data Ingestion

- Parses `restaurant.json`.
- Converts raw data into LangChain Documents.
- Enriches text with metadata fields (Cuisine, Location, Price) for hybrid filtering.

Step 2: Embedding Generation

- **Model:** Local HuggingFace (`all-MiniLM-L6-v2`).
- **Process:** Converts text to vectors on the CPU.
- **Benefit:** Zero cost and full data privacy.

Step 3: Retrieval Strategy (Hybrid Search)

The system combines two search methods to ensure accuracy:

1. **Semantic Search:** Finds matches based on meaning (e.g., "cozy" matches description text).
2. **Metadata Filtering:** Filters based on hard constraints (e.g., "Cuisine = Italian").
3. **Thresholding:** Only returns results with a similarity score > 0.3 to reduce hallucinations.

Step 4: Generation

- Constructs a prompt with the retrieved context.
- Sends the prompt to Groq (Llama 3.1).
- Returns a natural language response formatted as a helpful concierge.

5. Edge Case Handling & Production Readiness

- **No Results Found:** System detects empty retrieval sets and returns a helpful fallback message ("I couldn't find exact matches, but here are some alternatives...").
- **API Reliability:** Includes error handling for Groq API timeouts or limits.
- **Cost Optimization:** The architecture incurs **\$0 operational costs** for the embedding layer by using local models.
- **Scalability:** ChromaDB is configured for persistence, allowing the system to restart without rebuilding the index.

6. Future Enhancements

- **Agent Integration:** Connect RAG to LangGraph agents for multi-step reasoning (Task 1.2).
- **Caching:** Implement Redis to cache frequent queries (e.g., "Italian food") to reduce LLM latency.
- **Re-ranking:** Add a Cross-Encoder step to re-rank retrieved results for higher precision.