RAG-LLM Efficiency Engine: A Generic Approach

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Problem

Large Language Models (LLMs) are powerful but can "hallucinate" or generate plausible but incorrect information, especially on specialized topics. They lack access to real-time or domain-specific knowledge beyond their training data.

Solution??

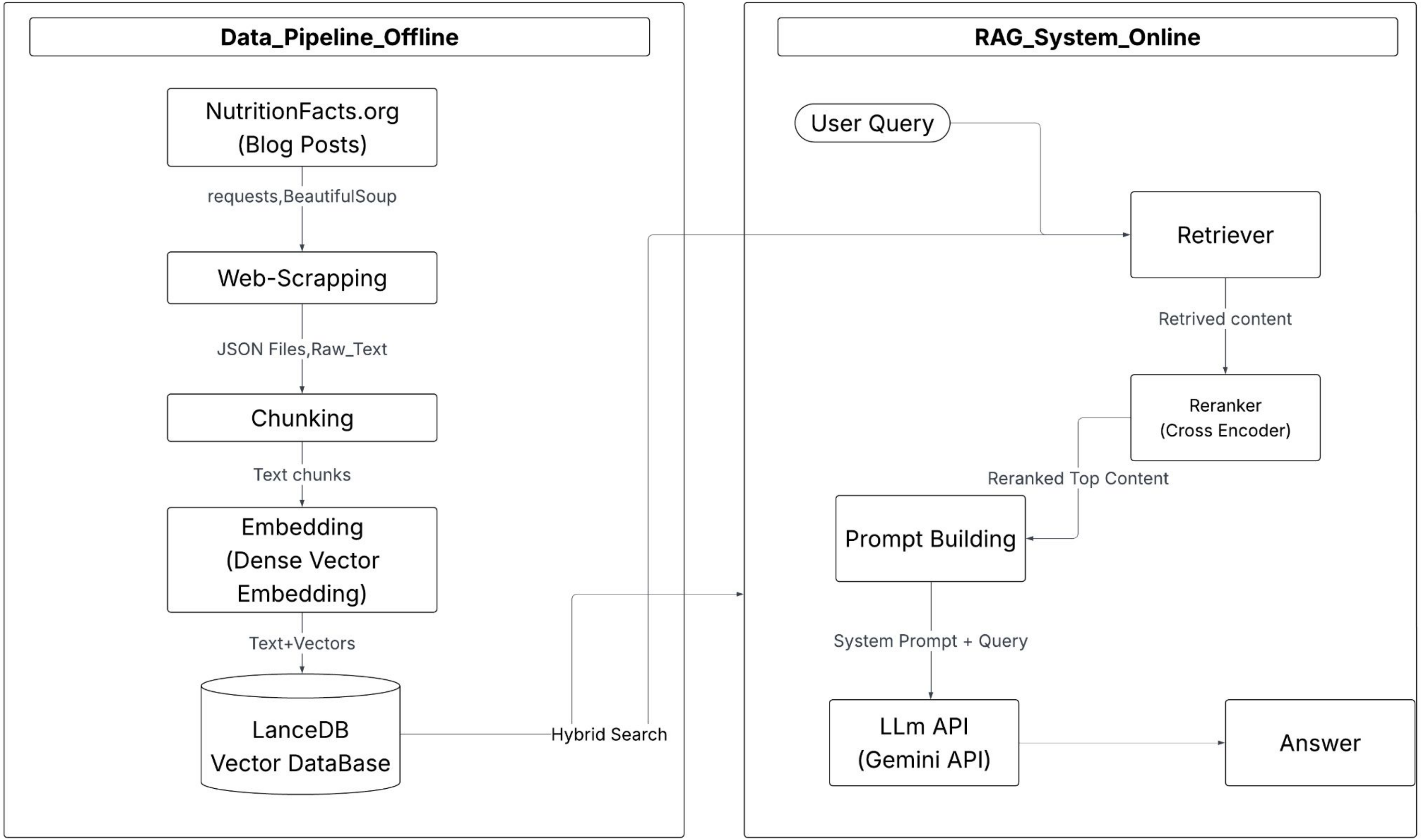
Retrieval-Augmented Generation (RAG) - A powerful architecture combining information retrieval with LLM generation.

What is RAG?

- **Retrieval:** It retrieves relevant snippets from a large knowledge base based on the user's query.
- **Augmentation:** It enriches the user's query or LLM prompt with retrieved context for better, accurate responses.
- **Generation:** An LLM generates an answer using both the original query and retrieved context, ensuring factual grounding.
- **Benefit:** Reduces hallucination, improves factual accuracy, allows grounding in specific/updated knowledge.

System Architecture: A Modular RAG Pipeline

1. **Data Preparation Pipeline:** Ingesting and preparing any text corpus for retrieval (Scraping/Loading ⟶ Chunking ⟶ Embedding ⟶ Vector Storage).
2. **RAG Core:** The real-time query processing flow (Query ⟶ Retrieve ⟶ Rerank ⟶ Augment Prompt ⟶ Generate).


Data_Pipeline_Offline
NutritionFacts.org
(Blog Posts)
requests,BeautifulSoup
Web-Scrapping
JSON Files,Raw_Text
Chunking
Text chunks
Embedding
(Dense Vector
Embedding)
Text+Vectors
LanceDB
Vector DataBase
Hybrid Search
RAG_System_Online
User Query
Retriever
Retrived content
Reranker
(Cross Encoder)
Reranked Top Content
Prompt Building
System Prompt + Query
LLm API
(Gemini API)
Answer

```
100%|██████████| 1248/1248 [01:31<00:00, 13.58it/s]
fts 1.0 2.0238782051282014
100%|██████████| 1248/1248 [02:51<00:00,  7.29it/s]
vector 0.8044871794871795 1.058506944444448
100%|██████████| 1248/1248 [03:15<00:00,  6.37it/s]
hybrid 0.9735576923076923 1.5301014957264971
```

Linear Combination

```
10 results for query
7 unique URL(s)
7 unique Title(s)
Paragraphs:
  1. (0.100) 'How to Eliminate 90 P
  2. (0.100) 'Why Don’t More Doctor
  3. (0.097) 'How to Eliminate 90 P
  4. (0.066) 'Magnesium-Rich Foods
  5. (0.065) 'How to Eliminate 90 P
  6. (0.063) 'How to Eliminate 90 P
  7. (0.036) 'The Most Anti-Inflamm
  8. (0.022) 'How to Eat to Reduce
  9. (0.021) 'Breast Cancer and Alc
 10. (0.019) 'How to Prevent Heart
```

Cross-Encoder Rearanker

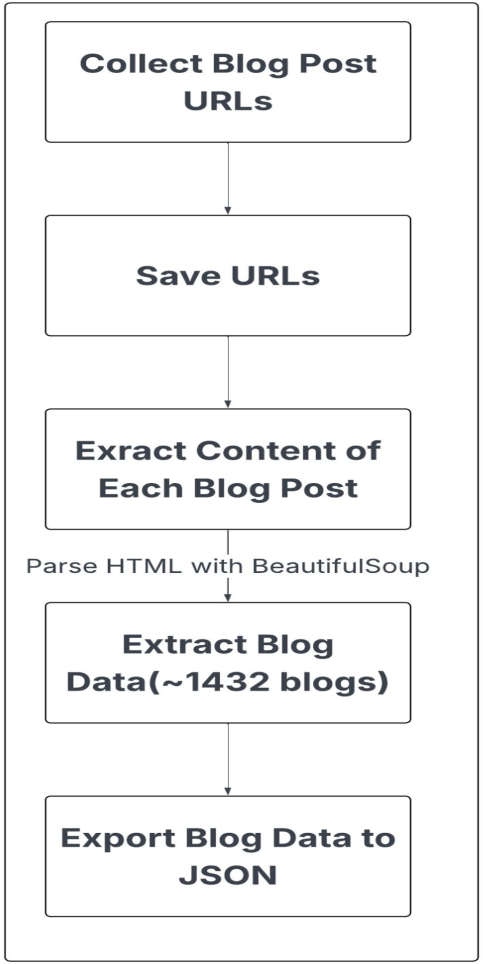
```
10 results for query
8 unique URL(s)
8 unique Title(s)
Paragraphs:
  1. (0.591) 'How to Prevent Heart Disea
  2. (0.591) 'How to Prevent Heart Disea
  3. (0.514) 'Breast Cancer and Alcohol:
  4. (0.254) 'The Most Anti-Inflammatory
  5. (0.084) 'How to Prevent Heart Disea
  6. (0.083) 'How to Eliminate 90 Percen
  7. (0.038) 'How Much Nutrition Educati
  8. (0.026) 'How to Treat High Lp(a), a
  9. (0.017) 'Moderation Kills' : 'What
 10. (0.013) 'How to Eliminate 90 Percen
```

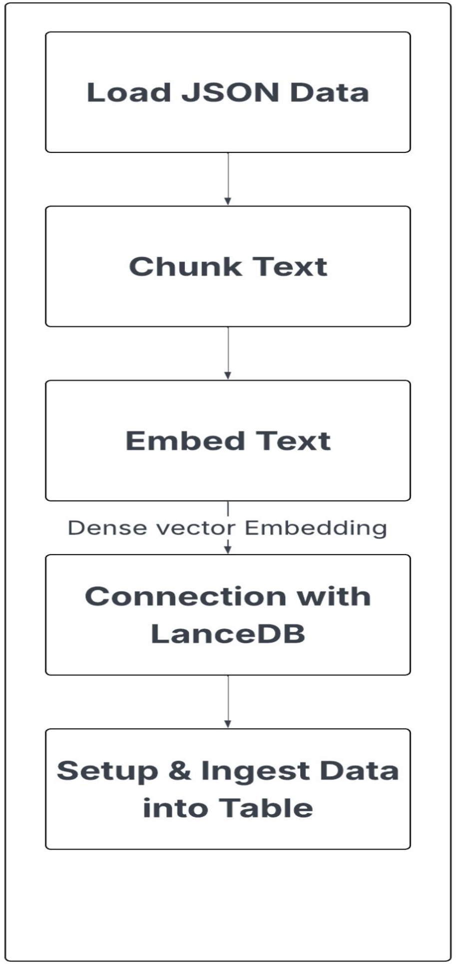
Results

Implementation - Data Preparation Pipeline

- **Objective:** Convert a raw text corpus into a searchable vector index.
- **Used example Corpus:** NutritionFacts.org blog posts.
- **Steps:**
  - **Ingestion:** Acquiring documents (e.g., via web scraping).
  - **Chunking:** Breaking documents into smaller, semantically meaningful units.
  - **Embedding:** Transforming text chunks into dense vector representations using Sentence Transformer.
  - **Vector Storage:** Loading vectors and associated metadata into LanceDB.

WEB SCRAPING

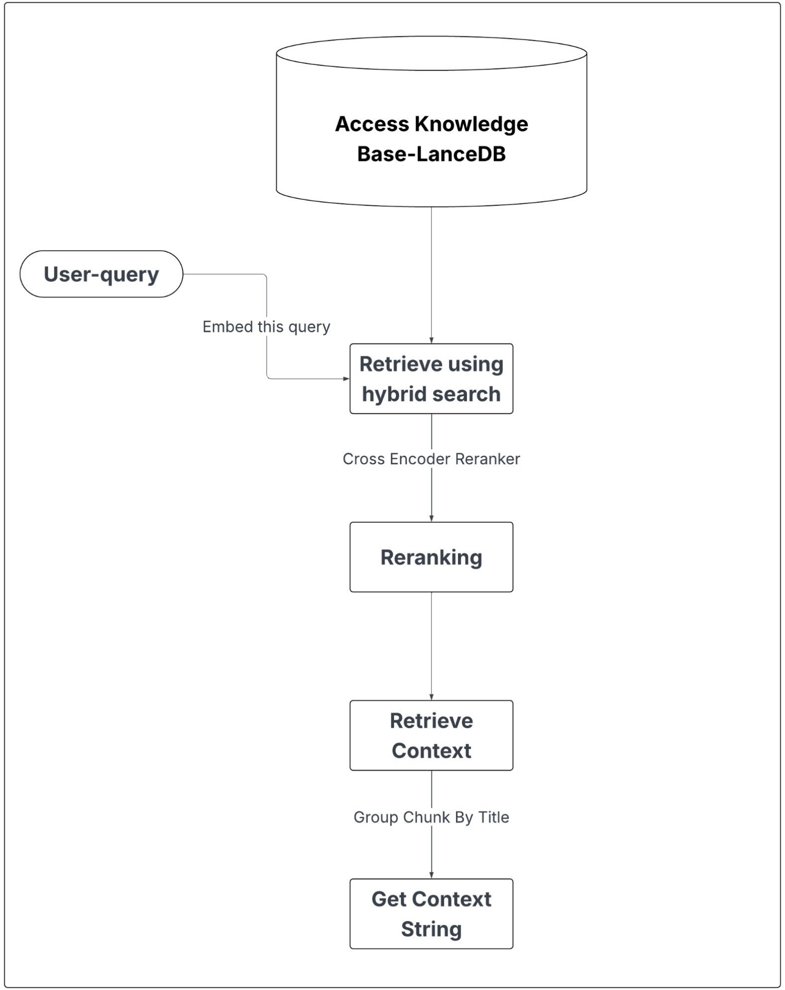


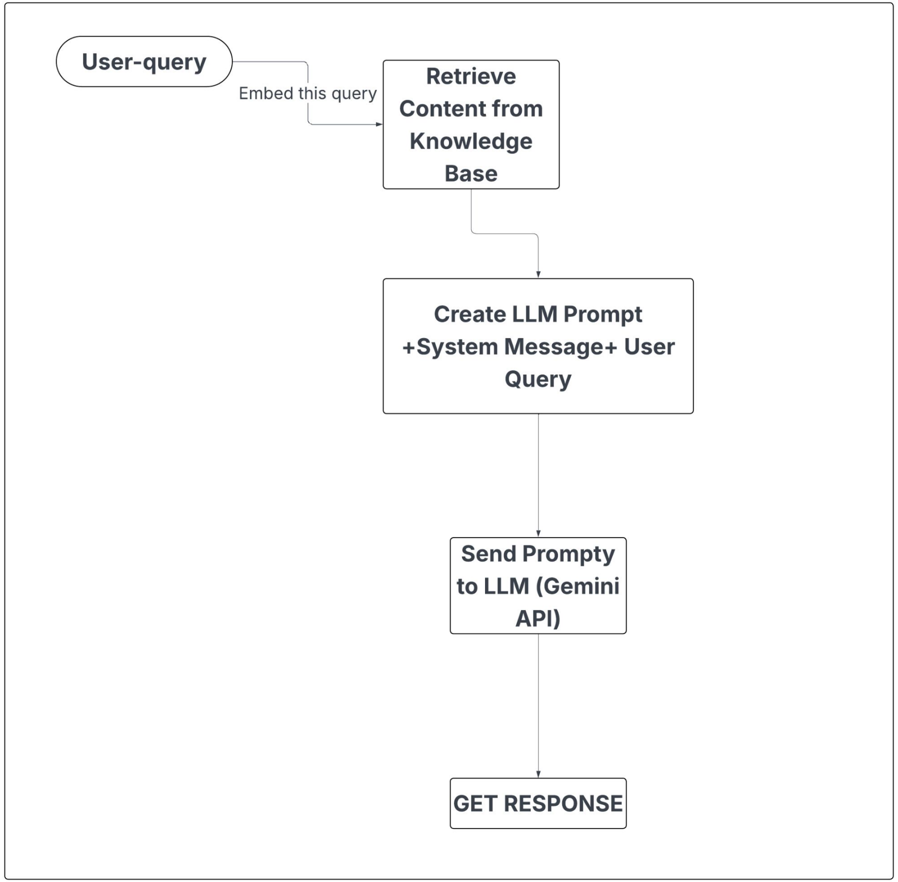


DATA INGESTION

Implementation - RAG Core: Retrieval & Reranking

- **Goal:** Identify the most relevant text chunks for the input query from the Vector DB.
- **Initial Retrieval**
  - Using Hybrid Search in LanceDB (combining keyword and vector similarity) for broad recall.
- **Reranking**
  - *Why Rerank?* Initial retrieval prioritizes speed/recall; reranking refines precision using more computationally intensive models.
  - Method: Employing a CrossEncoderReranker to re-score the top candidates based on deeper semantic relevance to the query.

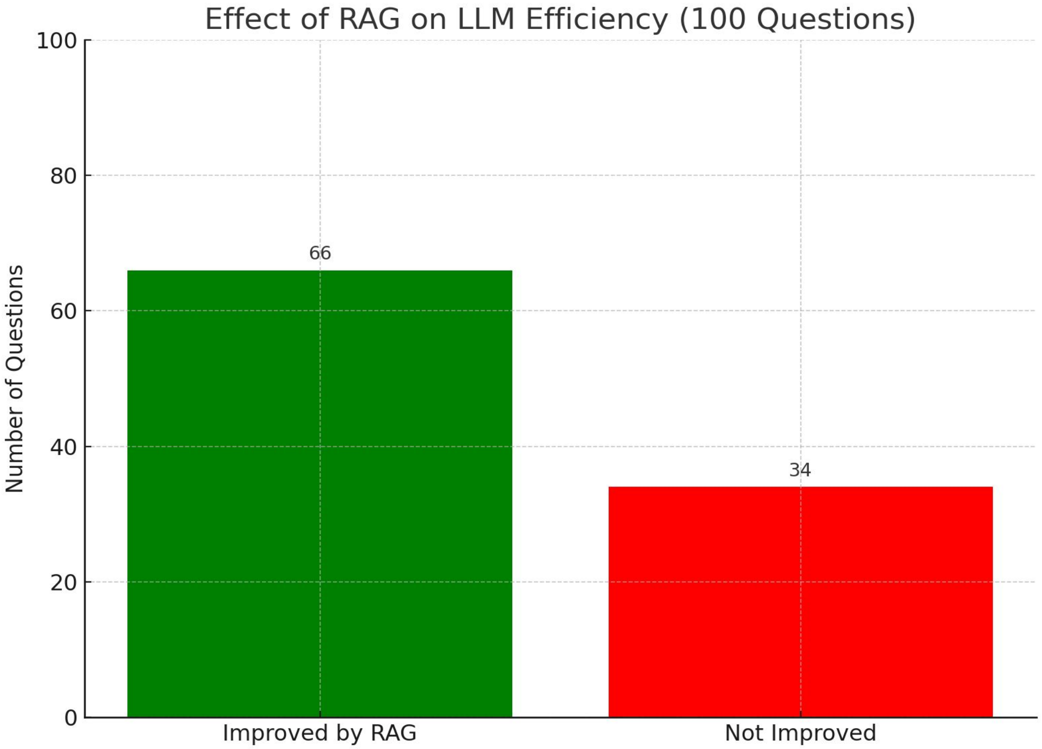

Access Knowledge Base-LanceDB
User-query
Embed this query
Retrieve using hybrid search
Cross Encoder Reranker
Reranking
Retrieve Context
Group Chunk By Title
Get Context String


User-query
Embed this query
Retrieve Content from Knowledge Base
Create LLM Prompt +System Message+ User Query
Send Prompty to LLM (Gemini API)
GET RESPONSE

Implementation - RAG Core: Generation

- **Goal:** Generate a final answer grounded in the retrieved and reranked context.
- **Prompt Augmentation**
  - Constructing a specific prompt for the LLM, incorporating the top N retrieved text chunks as context.
  - Instructing the LLM to base its answer solely on the provided context.
- **LLM Integration**
  - Utilizing the LLM API for efficient generation with models.
- **Demonstration**

Results



Effect of RAG on LLM Efficiency (100 Questions)
100
80
60
40
20
0
Number of Questions
66
34
Improved by RAG
Not Improved

Challenges & Learnings (Focus on RAG)

- **RAG-Specific Challenges:**
  - Optimizing chunk size (too small = loss of context, too large = noise).
  - Balancing retrieval and the role of reranking.
  - Prompt engineering to effectively instruct the LLM to use context.
- **Key Learnings:** RAG is a powerful but modular architecture requiring careful tuning of each component (embedding, retrieval, reranking, prompting) for optimal performance.

Thank You & Questions