

**Material :**      **Generative AI**

**Topic     :**      **RAG (Retrieval Augmented Generation)**



**Daniel**  
**danielgenai77@gmail.com**

# Gen AI – RAG (Retrieval Augmented Generation)

---

## Gen AI – RAG (Retrieval-Augmented Generation)

<b>1. RAG</b>	2
<b>2. Why RAG?</b>	2
<b>3. RAG Architecture: Step by step</b>	3
3.1. Encode Docs	3
3.2. Index	3
3.3. Encode Query	3
3.4. Similarity Search:	3
3.5. Retrieve:	3
3.6. Prompt LLM:	3
3.7. Generate Response:	4
<b>4. RAG: Retrieval Augmented Generation</b>	5
4.1. Retrieval	5
4.2. Augmented	5
4.3. Generation	5
<b>5. Workflow of a RAG System</b>	6
5.1. Addition knowledge base	7
5.2. Create Chunks	7
5.3. Generate embeddings	8
5.4. Store embeddings in a vector database	8
5.5. User input query	9
5.6. Embed the query	9
5.7. Retrieve similar chunks	10
5.8. Re-rank Chunks	10
5.9. Generate Final Response	11
<b>6. Tool Stack for Building a RAG System</b>	12
6.1. LlamaIndex	12
6.2. Qdrant	12
6.3. Ollama	12
<b>7. RAG application using Llama 3.2</b>	13

### Gen AI – RAG (Retrieval-Augmented Generation)

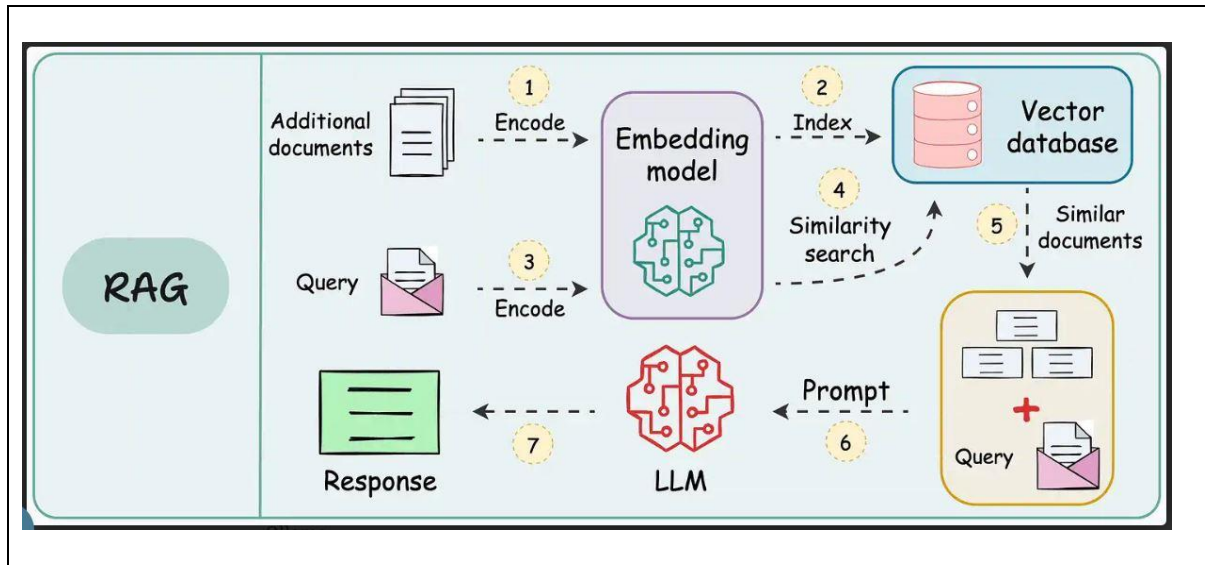
#### 1. RAG

- ✓ **RAG** stands for Retrieval-Augmented Generation.
- ✓ RAG is an NLP approach that:
  - **Retrieves** relevant info from external sources.
  - **Augments** the model input with that info.
  - **Generates** more accurate and factual responses using a language model.
- ✓ It helps LLMs handle large or constantly changing knowledge bases more effectively.
- ✓ RAG in GenAI = **Search + Generate**.
  - It gives large language models "open-book access" to relevant information, making them smarter, safer, and more adaptable.

#### 2. Why RAG?

- ✓ LLMs often lack up-to-date or specific knowledge.
- ✓ RAG solves this by retrieving relevant information from external sources and adding it to the prompt.
- ✓ This allows the LLM to generate more accurate, grounded, and context-aware responses.
- ✓ Here RAG helps.

### 3. RAG Architecture: Step by step



#### 3.1. Encode Docs

- ✓ Convert documents into embeddings using an embedding model.

#### 3.2. Index

- ✓ Store those embeddings in a vector database.

#### 3.3. Encode Query

- ✓ Convert the user query into an embedding.

#### 3.4. Similarity Search:

- ✓ Search the vector DB for documents similar to the query.

#### 3.5. Retrieve:

- ✓ Get the top matching documents.

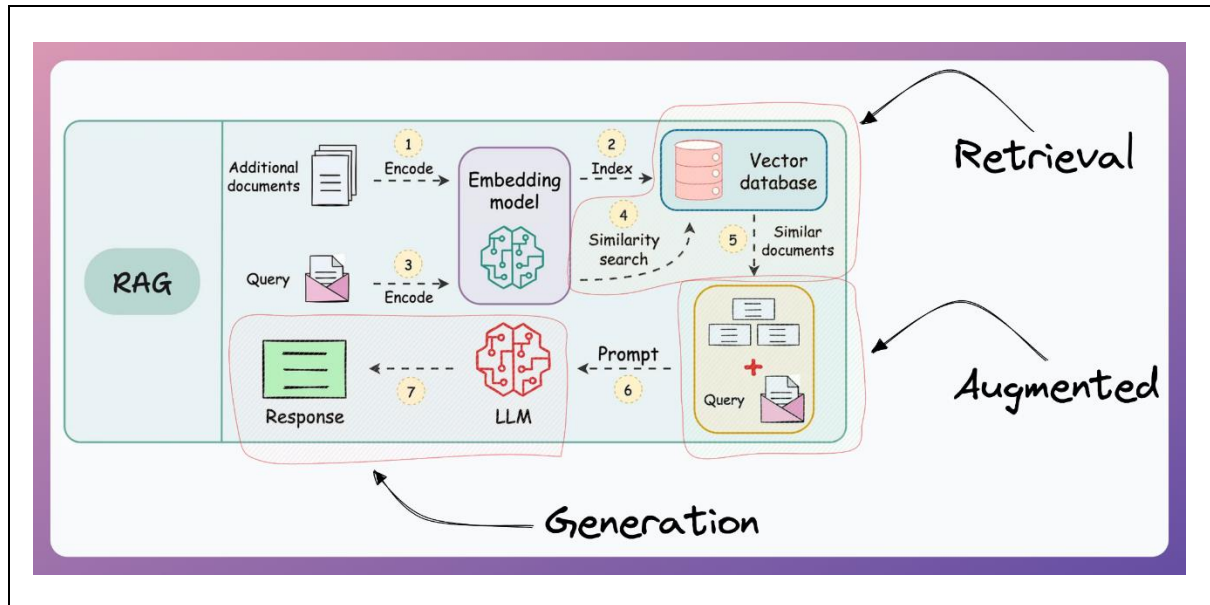
#### 3.6. Prompt LLM:

- ✓ Combine the retrieved documents with the query and send to the language model.

### 3.7. Generate Response:

- ✓ The LLM generates a final answer based on the augmented input.

### 4. RAG: Retrieval Augmented Generation



#### 4.1. Retrieval

- ✓ Fetching relevant info from a source (e.g., database).

#### 4.2. Augmented

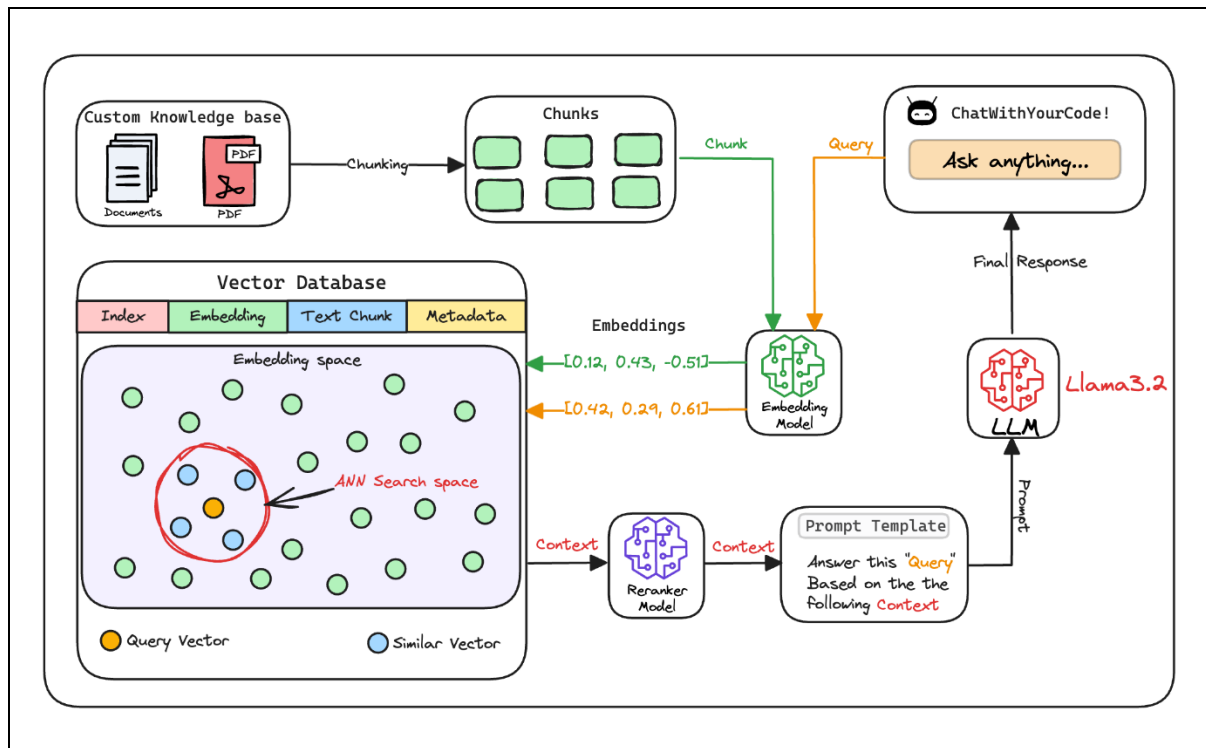
- ✓ Adding extra context to improve the process (e.g., text generation).

#### 4.3. Generation

- ✓ Creating or producing something, like generating text.

# Gen AI – RAG (Retrieval Augmented Generation)

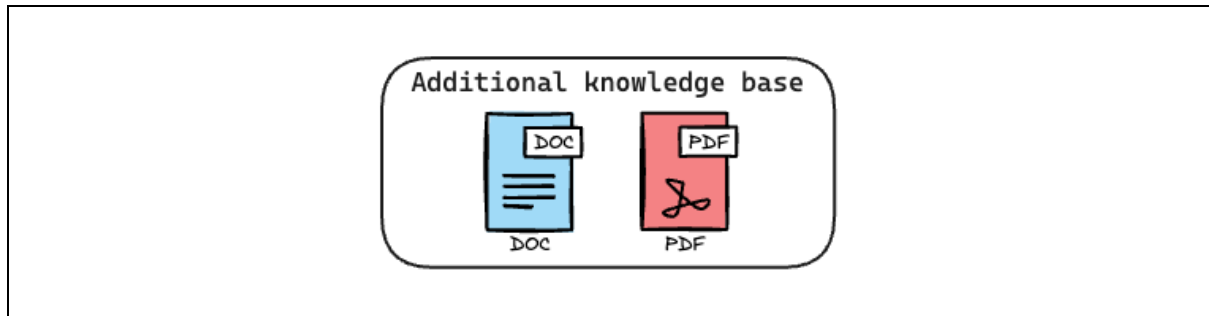
## 5. Workflow of a RAG System



## Gen AI – RAG (Retrieval Augmented Generation)

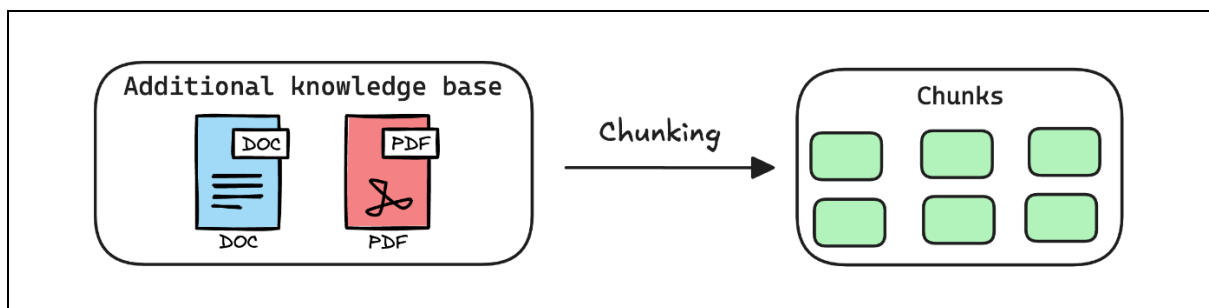
### 5.1. Addition knowledge base

- ✓ We start with some external knowledge that wasn't seen during training, and we want to enhance the LLM.



### 5.2. Create Chunks

- ✓ Before storing knowledge, it's broken into smaller, meaningful chunks.
- ✓ This improves retrieval accuracy and ensures each piece of information is easily searchable during query time.

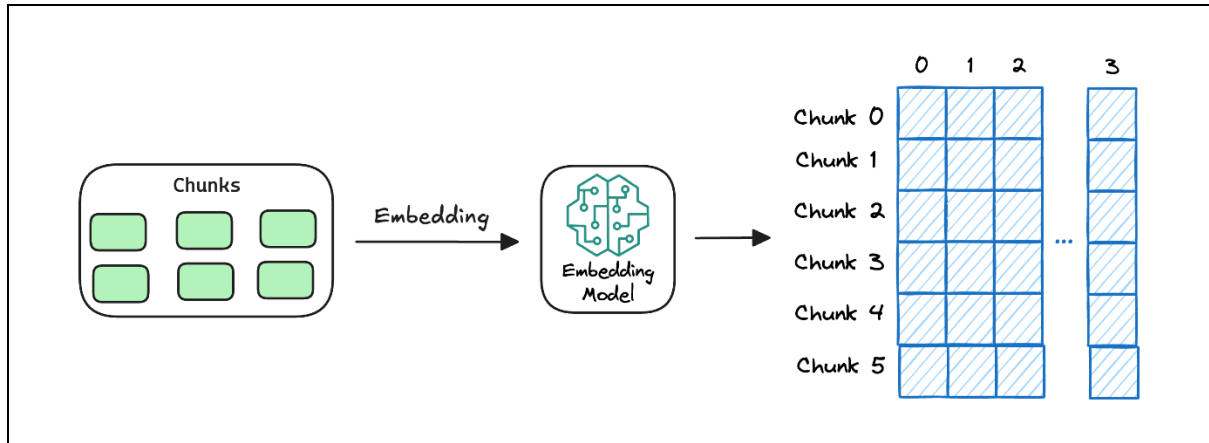




## Gen AI – RAG (Retrieval Augmented Generation)

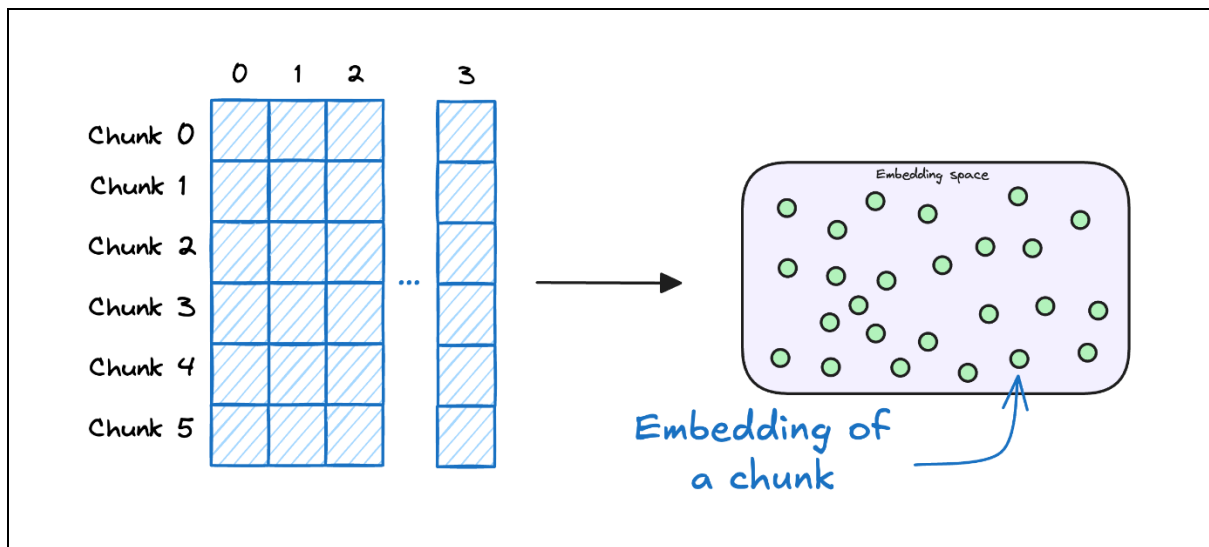
### 5.3. Generate embeddings

- ✓ After chunking, we embed the chunks using an embedding model.



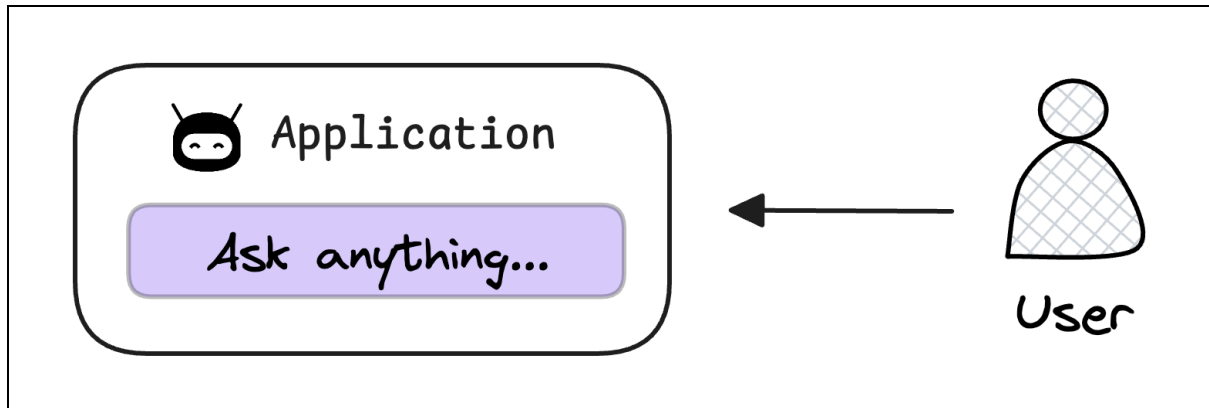
### 5.4. Store embeddings in a vector database

- ✓ These embeddings are then stored in the vector database



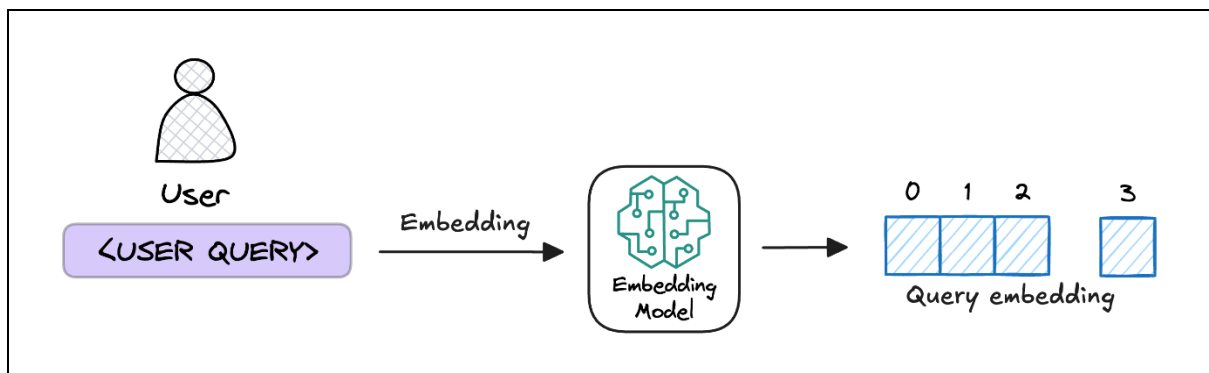
### 5.5. User input query

- ✓ Next, the user inputs a query, a string representing the information they're seeking.



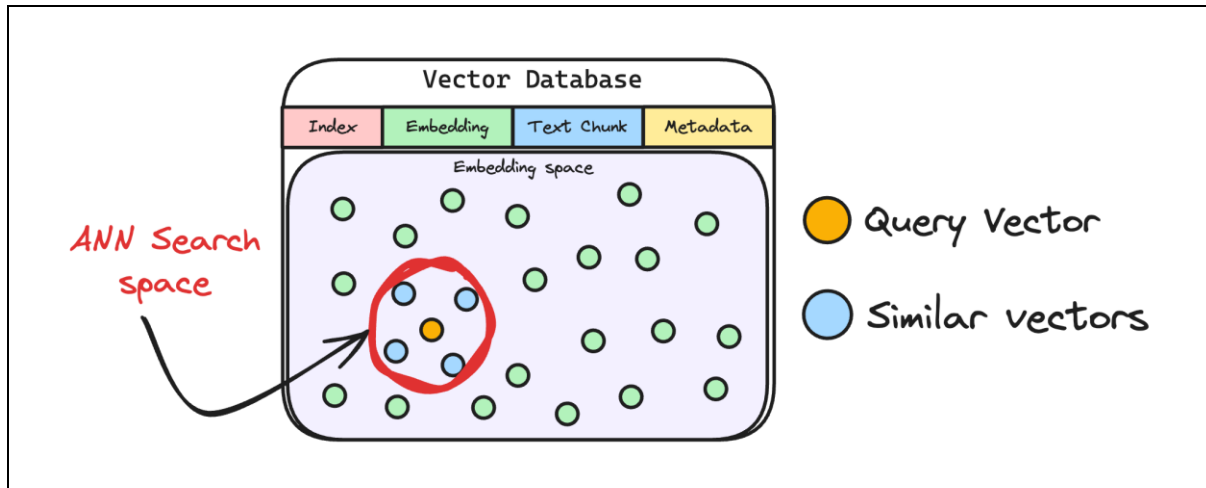
### 5.6. Embed the query

- ✓ This query is transformed into a vector using the same embedding model we used to embed the chunks earlier in Step 2.



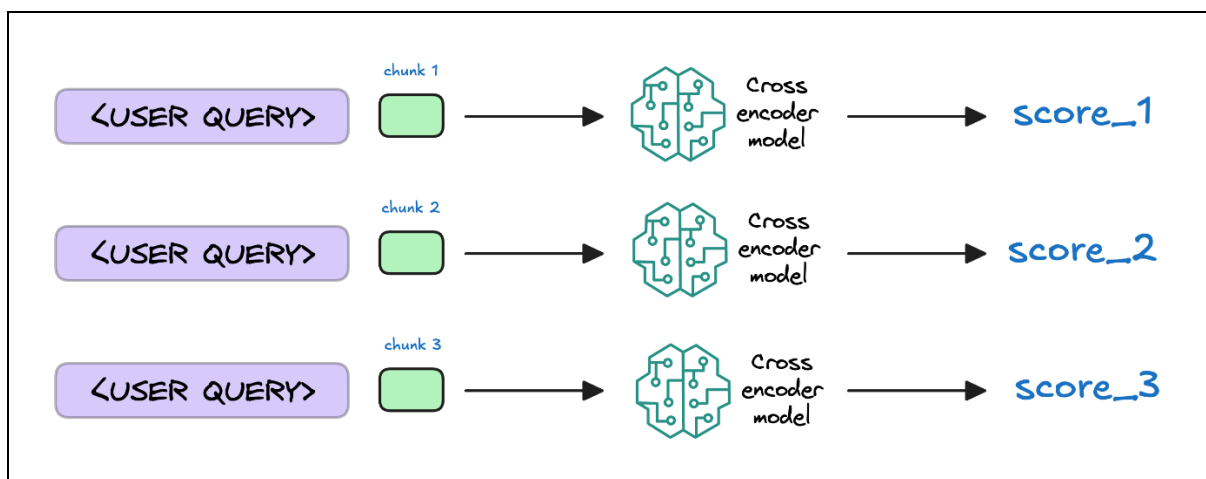
### 5.7. Retrieve similar chunks

- ✓ The vectorized query is then compared against our existing vectors in the database to find the most similar information.



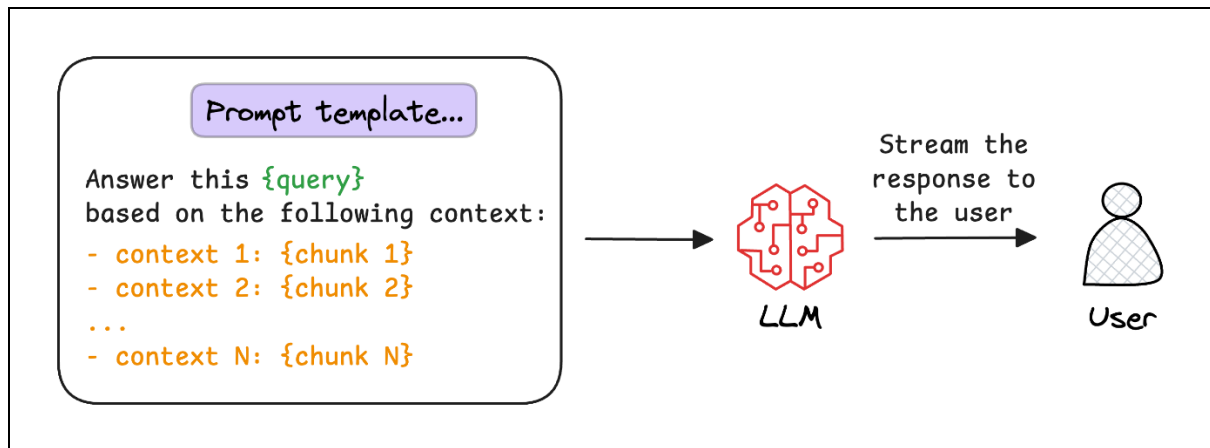
### 5.8. Re-rank Chunks

- ✓ After retrieval, a cross-encoder re-scores the chunks to prioritize the most relevant ones based on the query.



### 5.9. Generate Final Response

- ✓ The top-ranked chunks and the user query are combined into a prompt and sent to the LLM, which generates a final, informed response.



### 6. Tool Stack for Building a RAG System

#### 6.1. LlamaIndex

- ✓ Simplifies connecting LLMs with external data sources for indexing and querying.

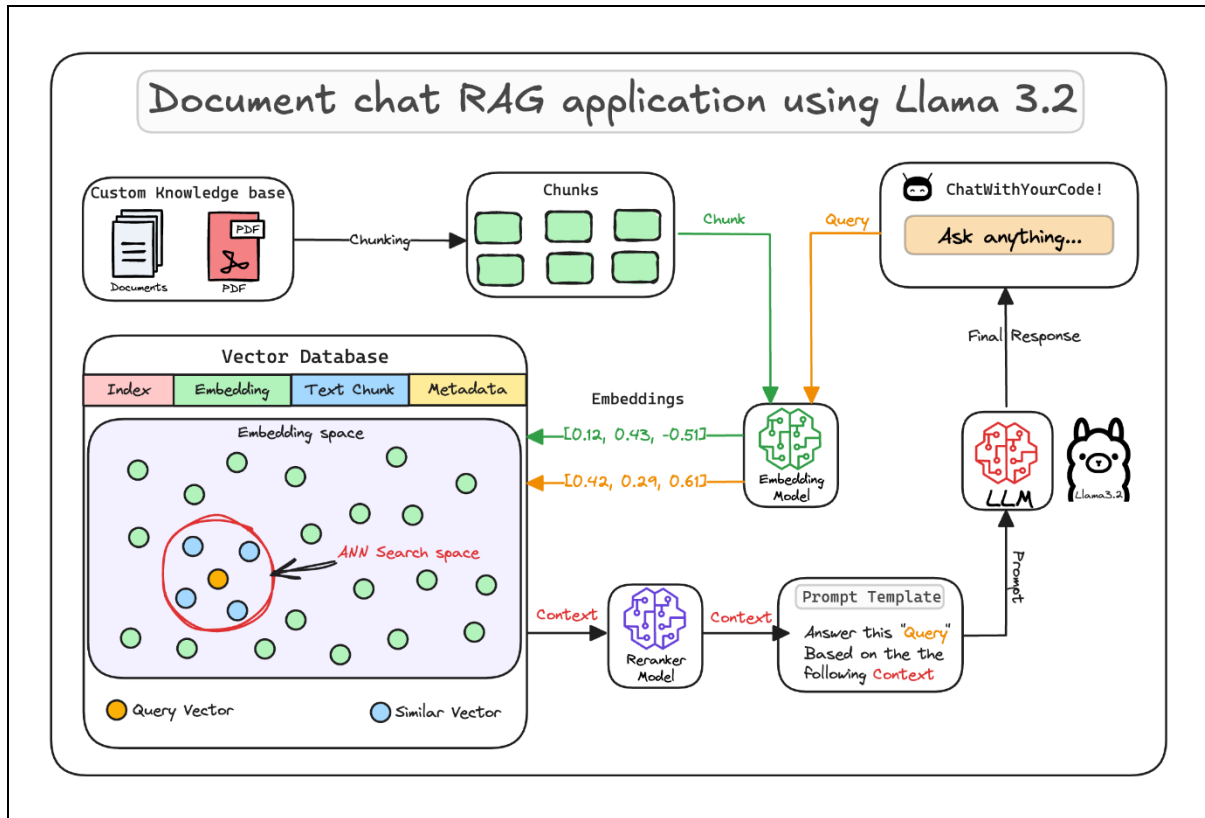
#### 6.2. Qdrant

- ✓ Open-source vector database for fast, filtered similarity search at scale.

#### 6.3. Ollama

- ✓ Runs LLMs locally, ideal for privacy-focused applications

## 7. RAG application using Llama 3.2



- ✓ **Custom Knowledge Base:** Input documents (e.g., PDFs, text files)
- ✓ **Chunking:** Break documents into smaller pieces (chunks)
- ✓ **Embedding:** Convert chunks into vector embeddings using an Embedding Model
- ✓ **Vector Database:** Store embeddings and related metadata. Perform ANN (Approximate Nearest Neighbor) search to find similar vectors to the user's query
- ✓ **Query Processing:** User submits a question. Convert query to a vector. Retrieve top matching chunks
- ✓ **Re-ranking (Optional):** Use a Re-ranker Model to refine and prioritize the most relevant chunks
- ✓ **Prompt Construction:** Fill a prompt template with the query and retrieved chunks
- ✓ **LLM Generation (Llama 3.2):** Final response is generated and shown to the user