

Retrieval Augmented Generation (RAG)

The information in this presentation is classified:

Google confidential & proprietary

1 This presentation is shared with you under <u>NDA</u>.

- Do **not** <u>record</u> or take <u>screenshots</u> of this presentation.
- Do **not** <u>share</u> or otherwise <u>distribute</u> the information in this presentation with anyone **inside** or **outside** of your organization.

Thank you!



In this module, you learn to ...

- Architect RAG solutions for real-world customer problems
- Choose the right embedding technology for creation, storage and serving
- Optimize workflows and RAG solutions



Topics

Q1 Retrieval Augmented Generation

RAG Optimization



Customer problem



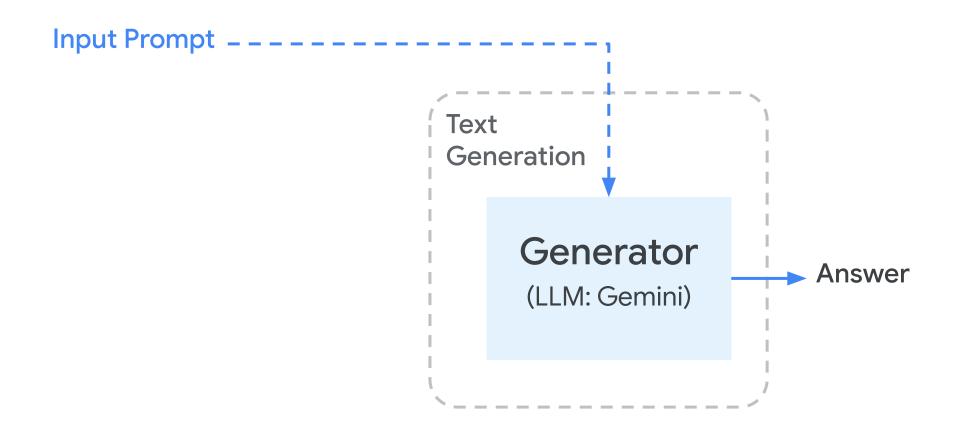
Provide semantic search to find answers from a proprietary dataset and obtain responses with summarizations grounded on the data

- Search answers should not paraphrase the stored data; they should answer the question
- Search answers should have a pointer to the document where the answer was found to be able to verify that answers are grounded on customer data
- Answers should not be made up if the data is not found in the search results
- Dataset is proprietary to the customer and it needs to stay private
- Dataset is constantly growing (it's not stale)

What is Retrieval Augmented Generation (RAG)?

The problem:

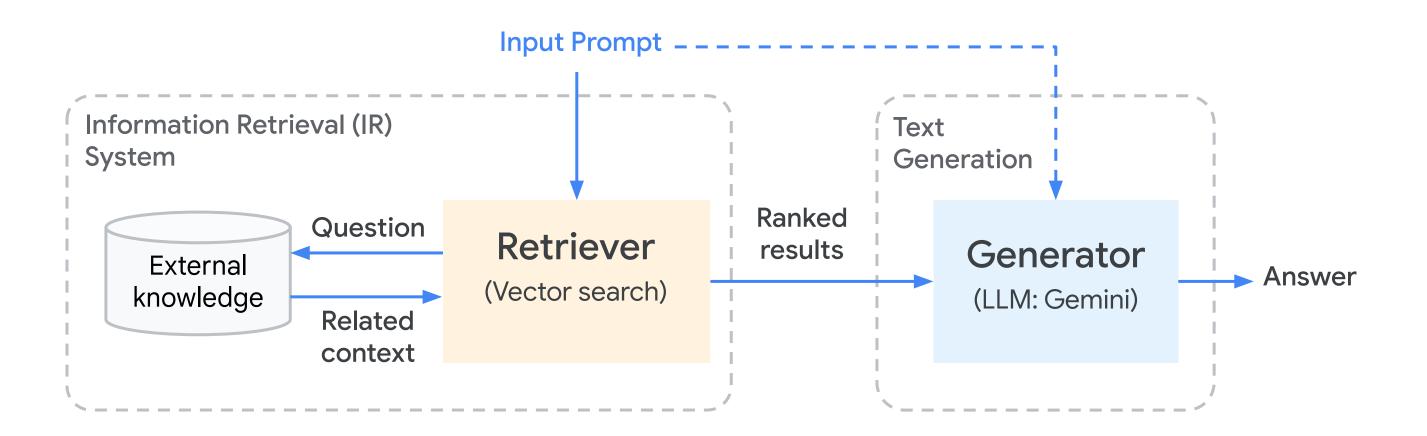
- LLMs don't know your business proprietary or domain specific data
- LLMs don't have real-time information
- LLMs find it hard to provide accurate citation



What is Retrieval Augmented Generation (RAG)?

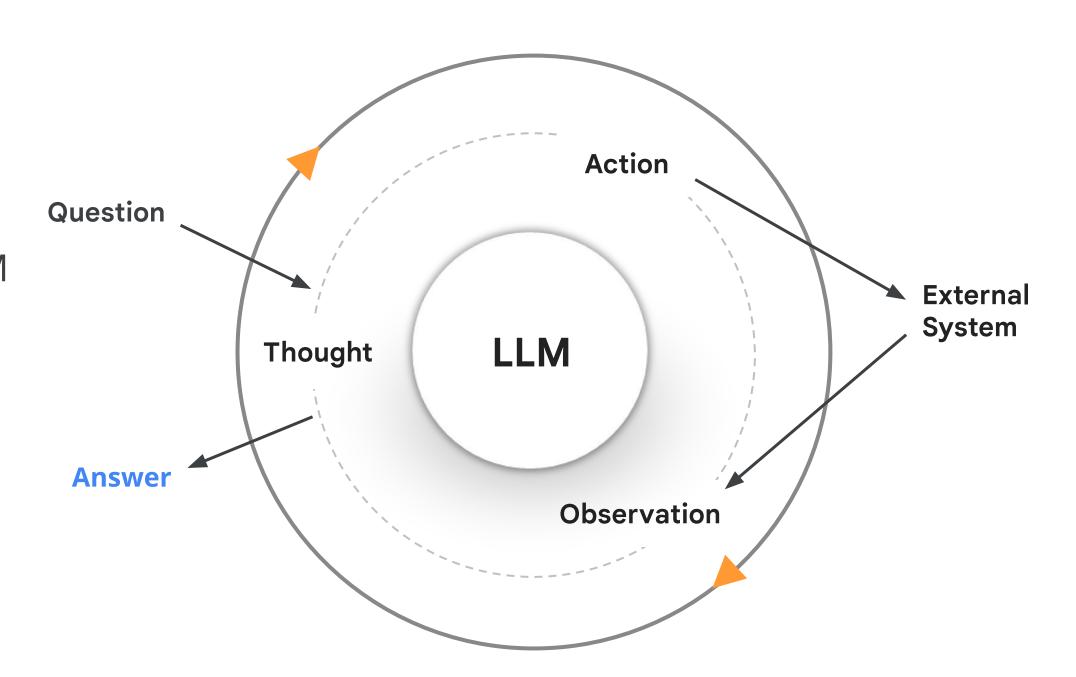
The solution:

• Feed the LLM relevant context in real-time, by using an information retrieval system

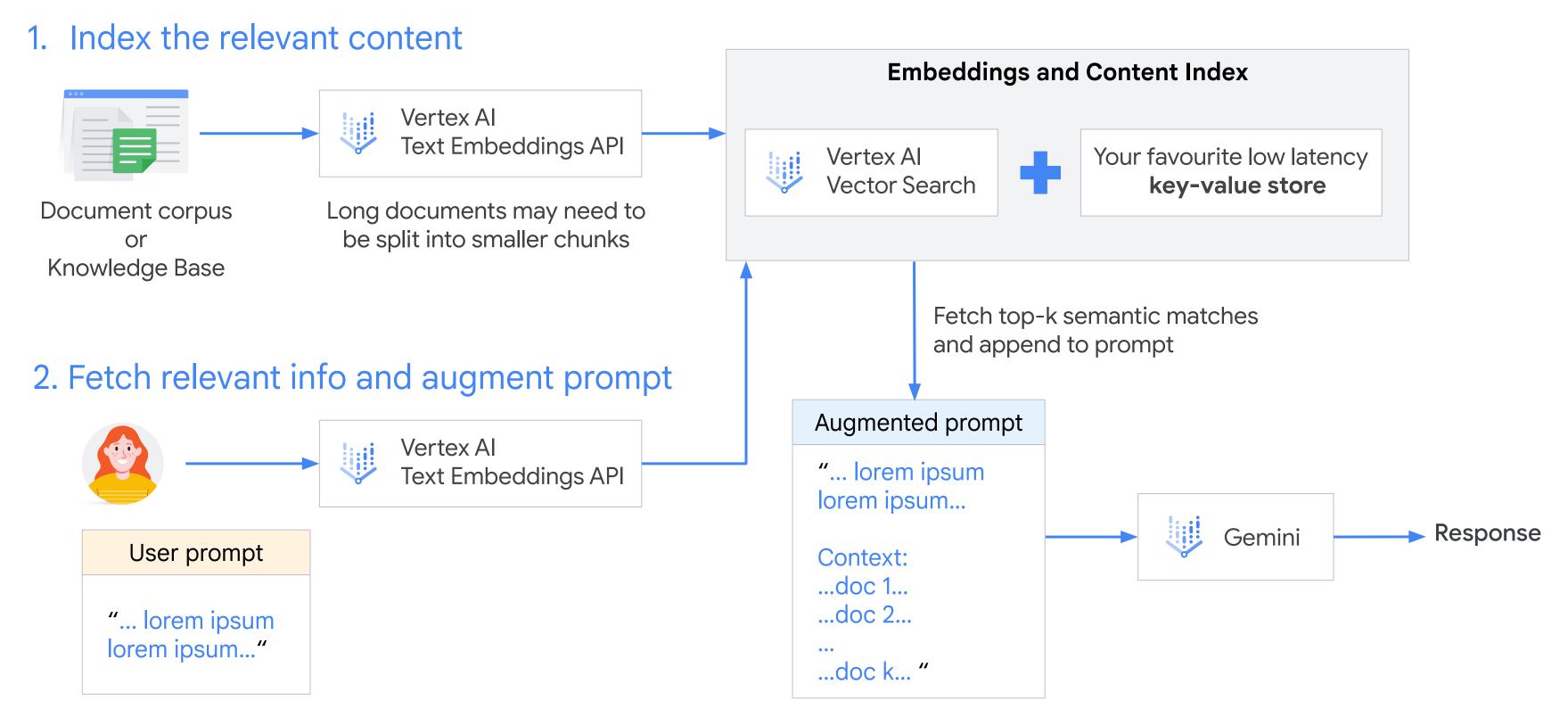


RAG is an implementation of the ReAct pattern

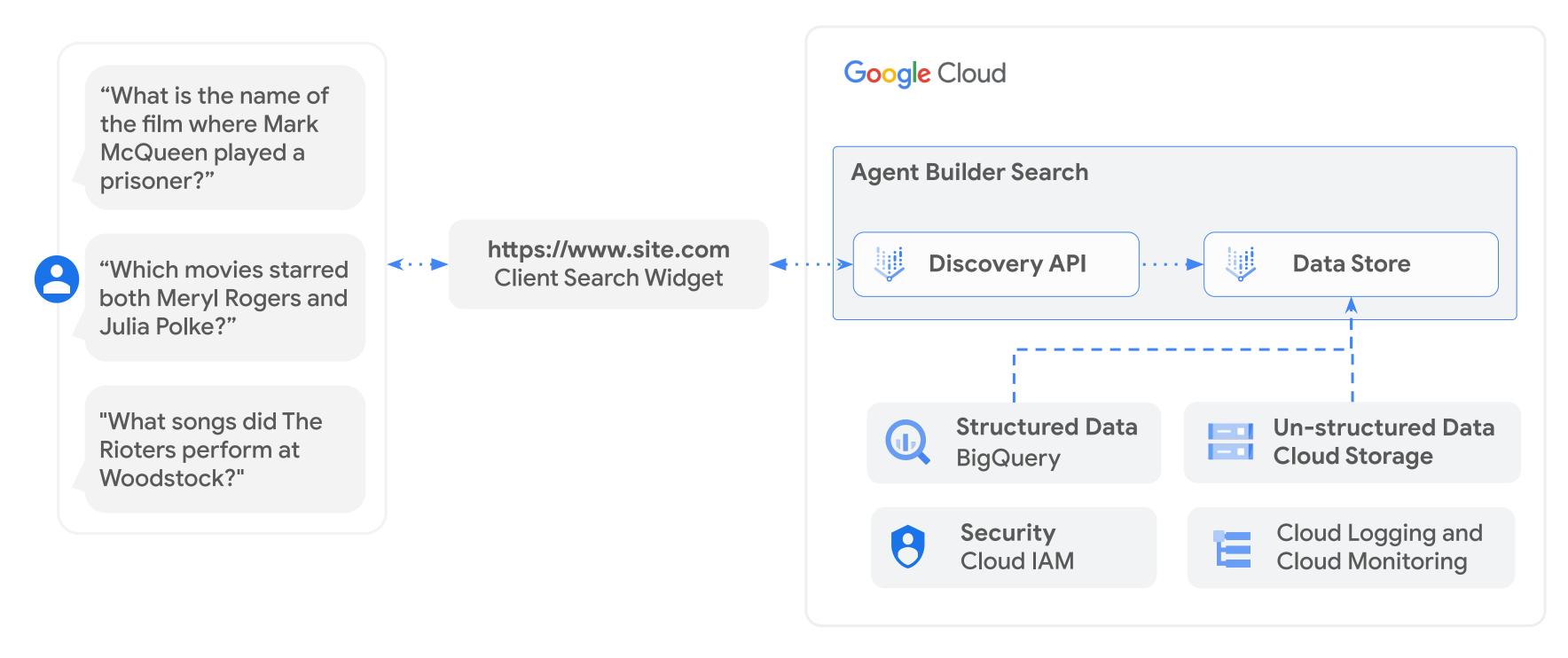
- A repository of data external to the LLM
- Embeddings and vector search to find the data relevant to a user query
- The LLM answers the question based on the data provided



RAG architecture example: embeddings and Vector Search



Automate RAG with Google Agent Builder Search Apps



Discussion out-of-the-box (OoTB) vs do-it-yourself (DIY)

Out-of-the-box

Agent Builder Search

Implementation in minutes

Only batch data refresh available

Supports:

- BigQuery tables, HTML, PDF with embedded text, TXT format
- Preview: PPTX and DOCX

Does not support: Images, videos, audio

Prompt templates in Preview

Do-it-yourself

Embeddings + Vector Search + Document Al

Implementation in hours or days

Batch and streaming data refresh available

Can be used with any data format

Parsing documents with Document AI before ingesting them as embeddings provides better outcomes than OOTB

Can create a prompt template and send it to the LLM

Benefits of RAG vs Fine Tuning



- You can use different versions of the LLM with the same knowledge base, without the need to re-train
- You can keep ingesting documents on-demand
- You can ground the answer in a specific known document source
- RAG is for supplying the LLM external data



Fine Tuning

- Fine tuning an LLM and keeping it up-to-date is more expensive than creating embeddings in RAG
- Inferencing in bigger fine-tuned LLMs can be more costly (sometimes) than an LLM with the context provided by the embedding
- Fine tuning is used to show the model how to format its answers

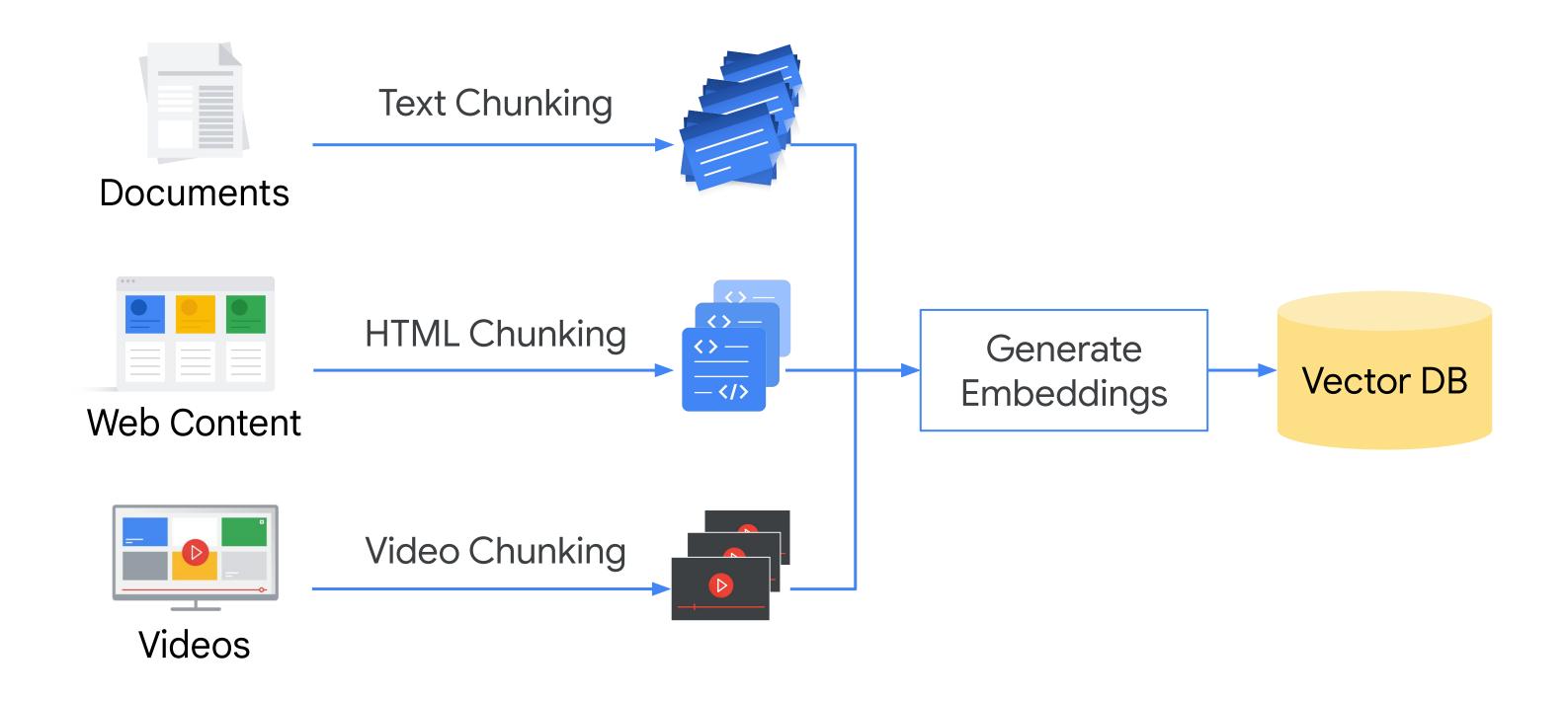
Topics

Q1 Retrieval Augmented Generation

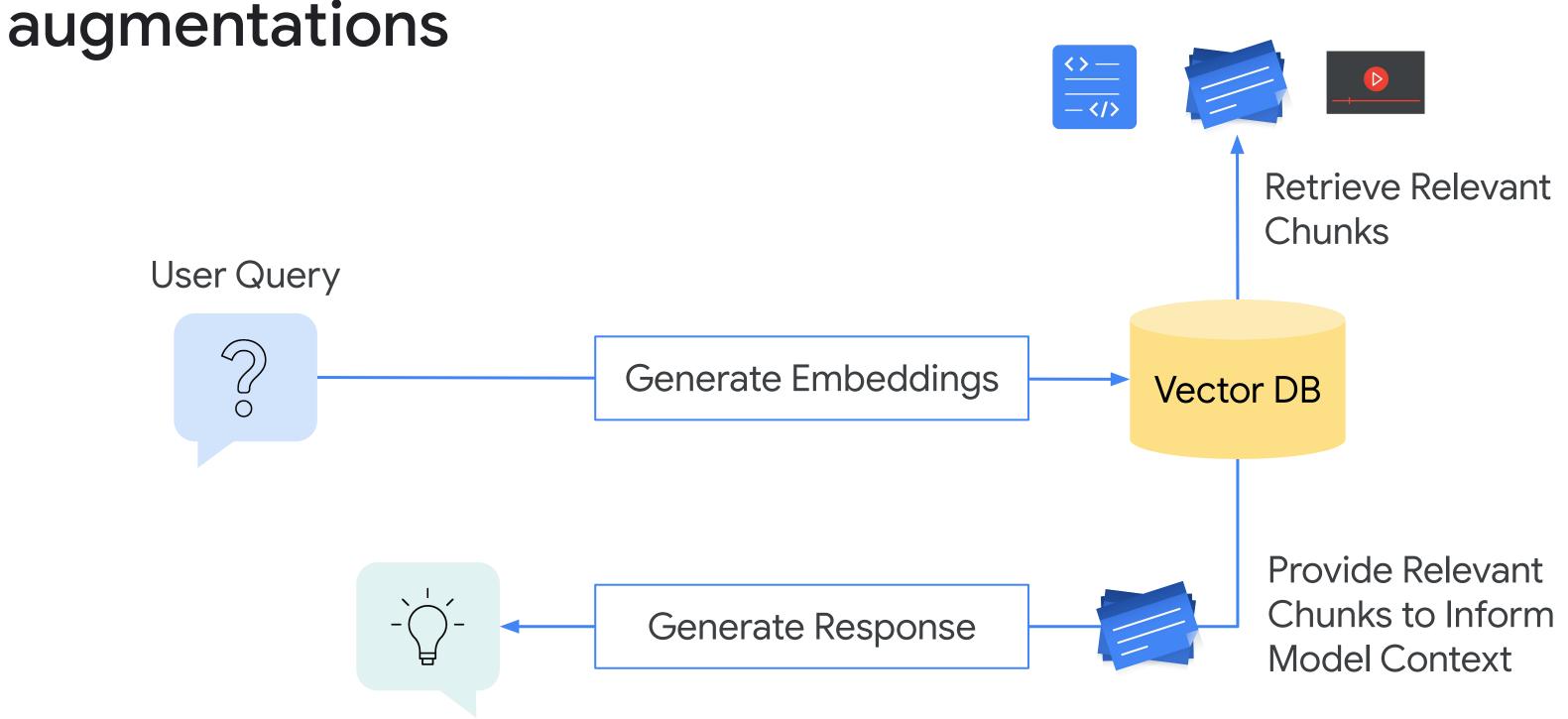
RAG Optimization



You can embed content from many types of source documents



Based on this basic RAG framework, let's consider some

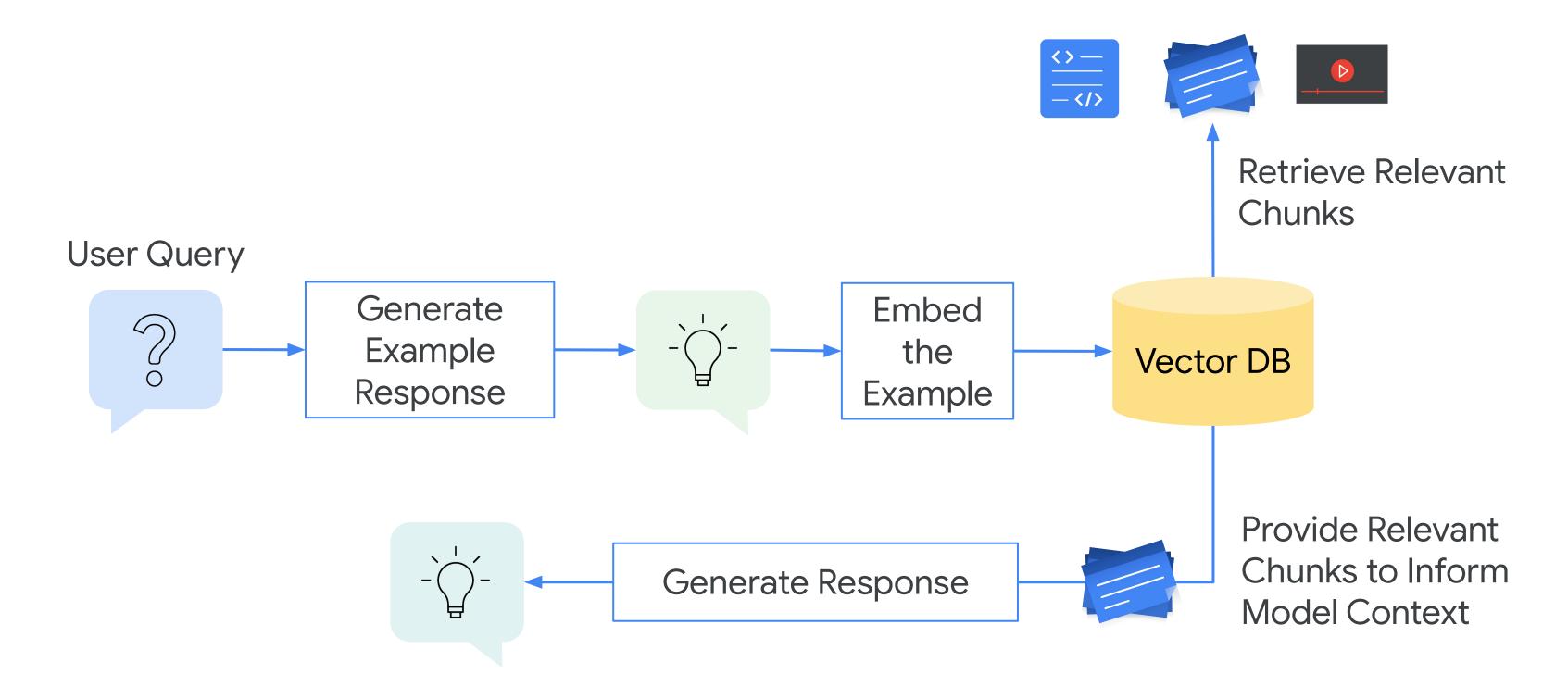


A response can look very different from a query

Why is the sky blue?

Sunlight reaches the atmosphere and is scattered in all directions...

RAG: HyDE (Hypothetical Document Embeddings)



There are also many ways to ask questions

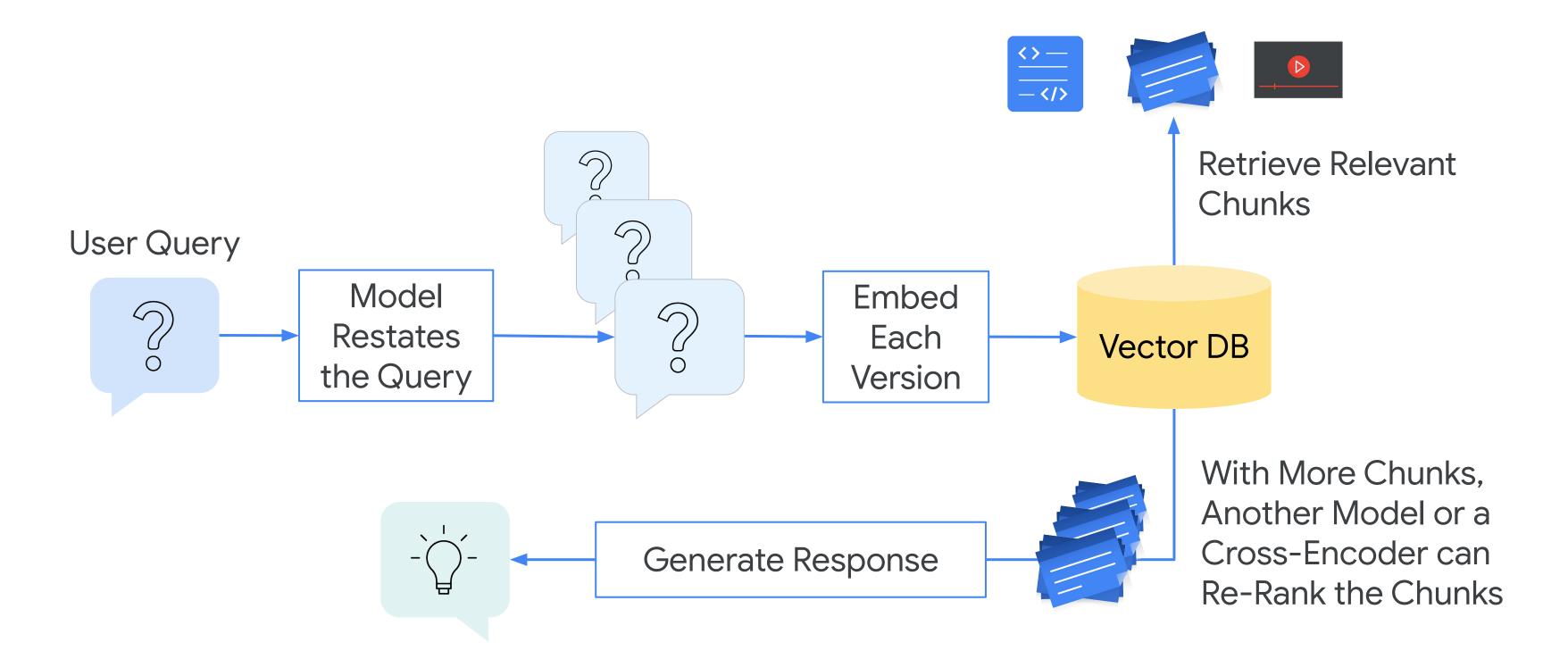
What were Bach's greatest accomplishments?

What was Bach's life like?

Tell me about Bach.

How has Bach impacted the world?

RAG: Query Expansion



You may also wonder what content informed a response



Which Documents?

We have 27 trucks in the fleet.

According to...



What Web Content?



Which Video(s)?

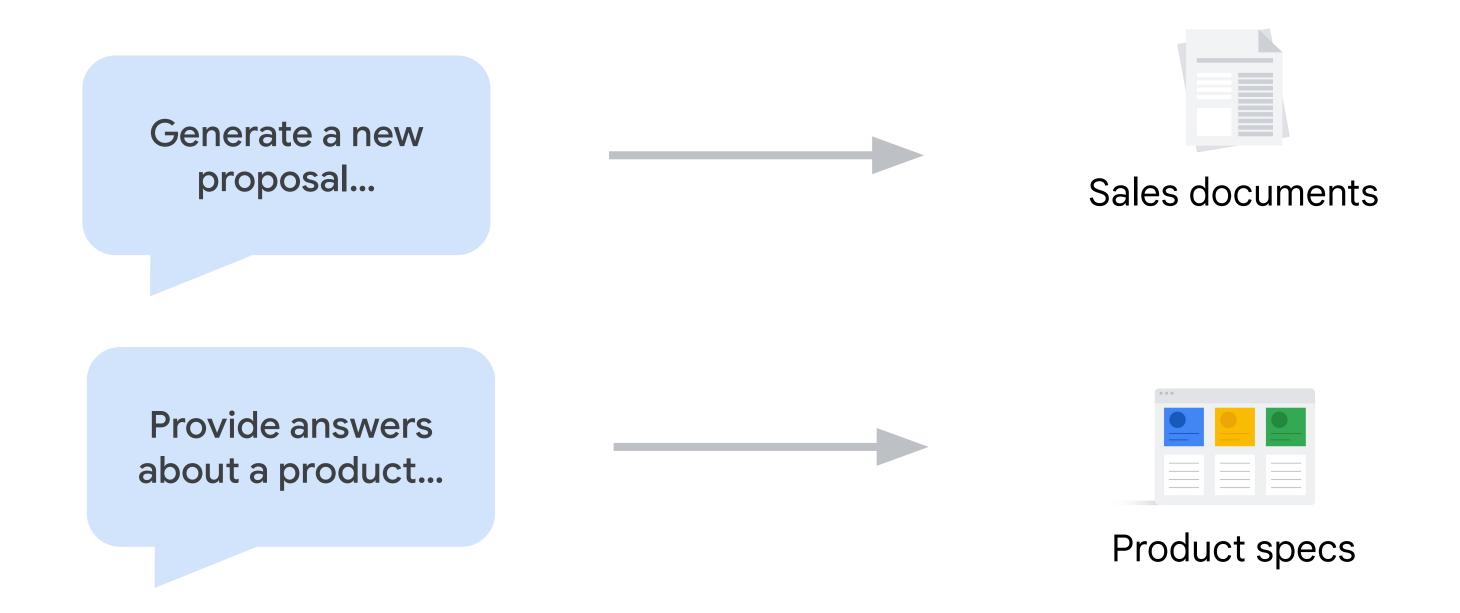
Include source metadata

RAG: Grounding

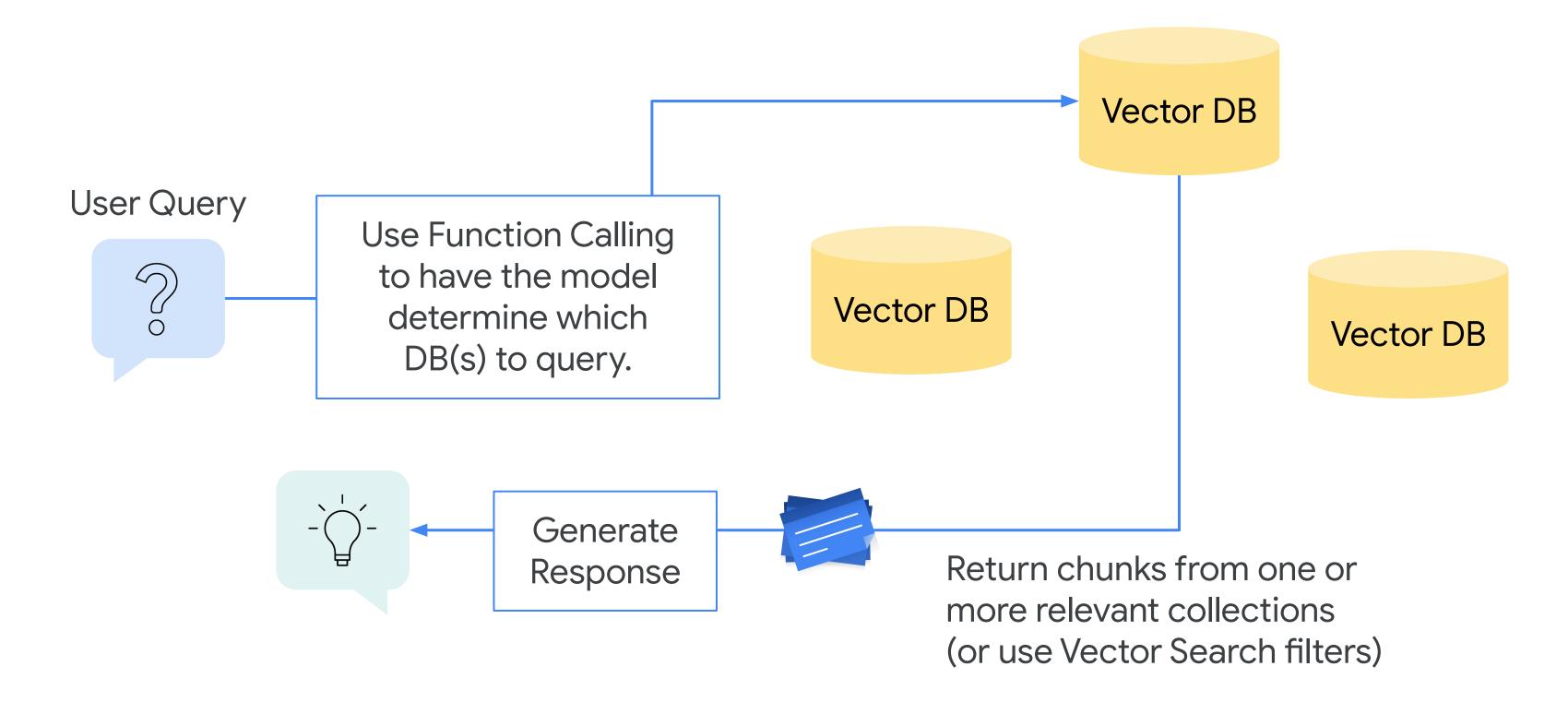
User Query Generate Embeddings Vector DB Generate Response Return source metadata and display

or instruct model to provide

You may want to provide context from different sources depending on the request

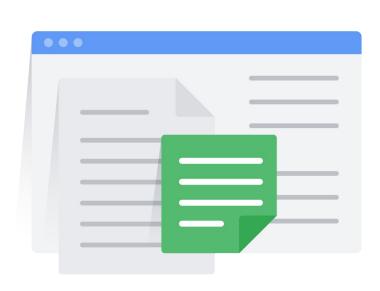


RAG: Routing

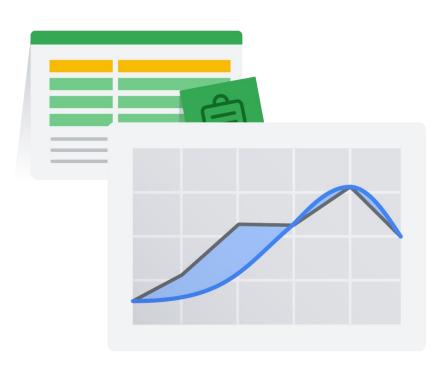


You may want to find answers in text or in images (plots or tables), this is called Multimodal RAG

How have our earnings changed in the last 6 quarters?

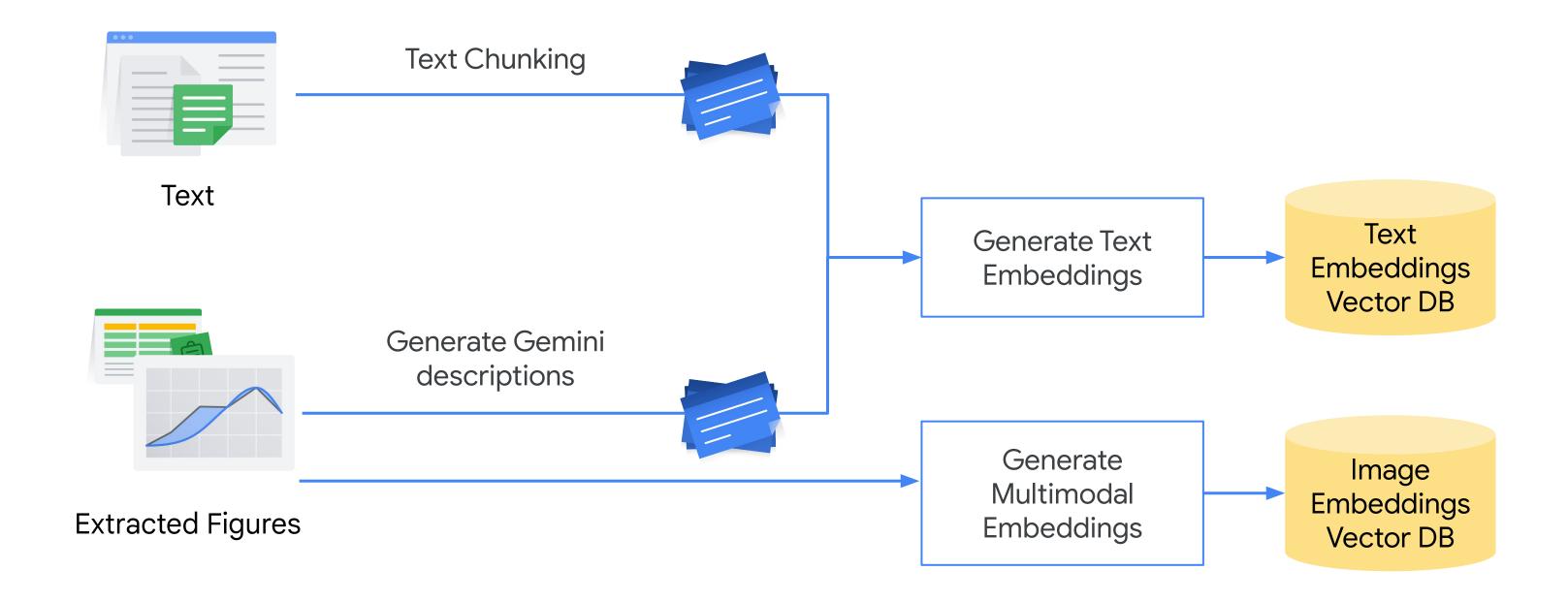


The answer could be in text...

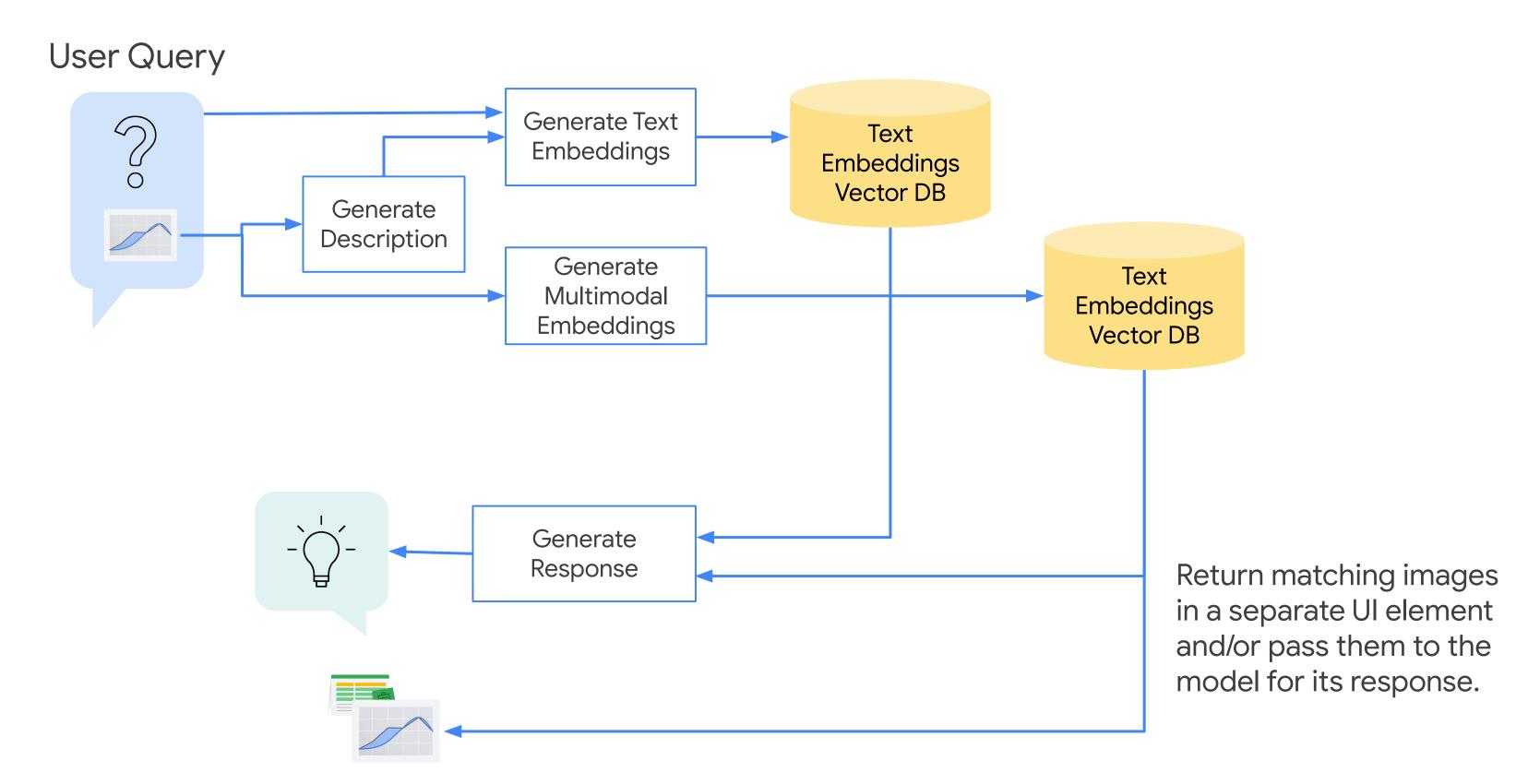


...or in an embedded table/plot.

Multimodal RAG: Generating the Databases



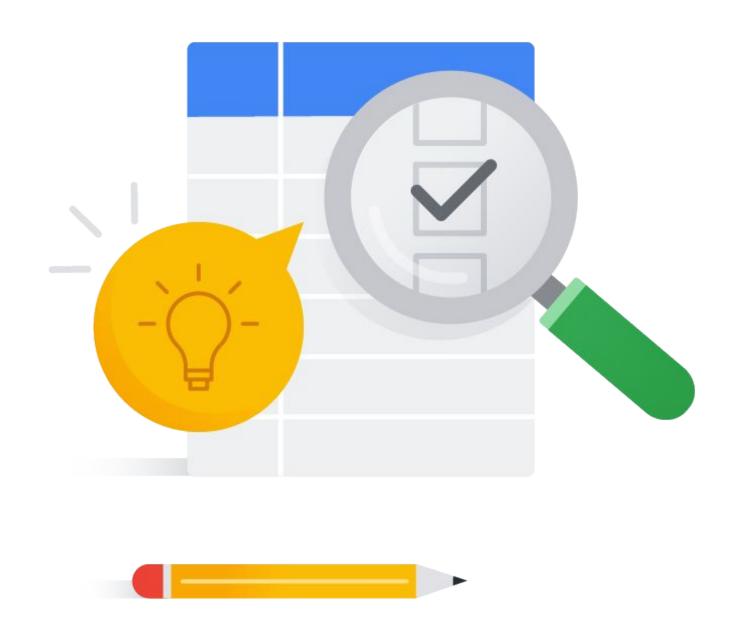
Multimodal RAG: Query Time



Lab



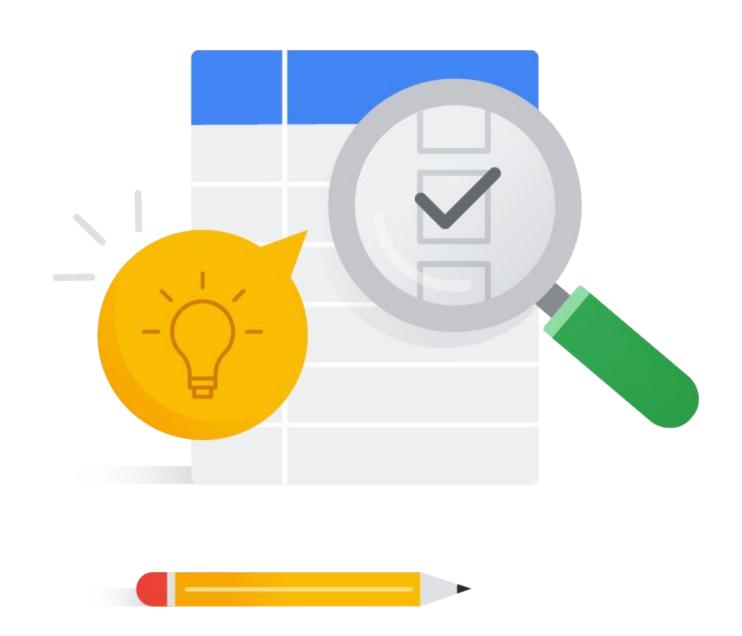
Lab: Using BigQuery Embeddings in a RAG Architecture



Lab



Lab: Multimodal Retrieval Augmented Generation (RAG) using the Vertex Al Gemini API



In this module, you learned to ...

- Architect RAG solutions for real-world customer problems
- Choose the right embedding technology for creation, storage and serving
- Optimize workflows and RAG solutions



Google Cloud