Generative AI Academy

Why customize?

- Lacks up to date / real time data
- Need it to be trained on proprietary / IP protected / subscription based datasets / documents
- Reduce hallucinations, improve accuracy and response, change the response

Multiple approaches available

- Prompt Engineering
  Refines model input to guide its output.
- Full Fine-tuning
  Adjusts all parameters of the LLM using task-specific data.
- Parameter-efficient Fine-tuning (PEFT)
  Modifies select parameters for more efficient adaptation.
- Retrieval Augmented Generation (RAG)
  Merges prompt engineering with database querying for context-rich answers.

Indexing

Indexing Pipeline

Data for the knowledge is ingested from the source and indexed. This involves steps like splitting, creation of embeddings and storage of data.

Loading

This step involves extracting information from different knowledge sources a loading them into documents.

Splitting

This step involves splitting documents into smaller manageable chunks. Smaller chunks are easier to search and to use in LLM context windows.

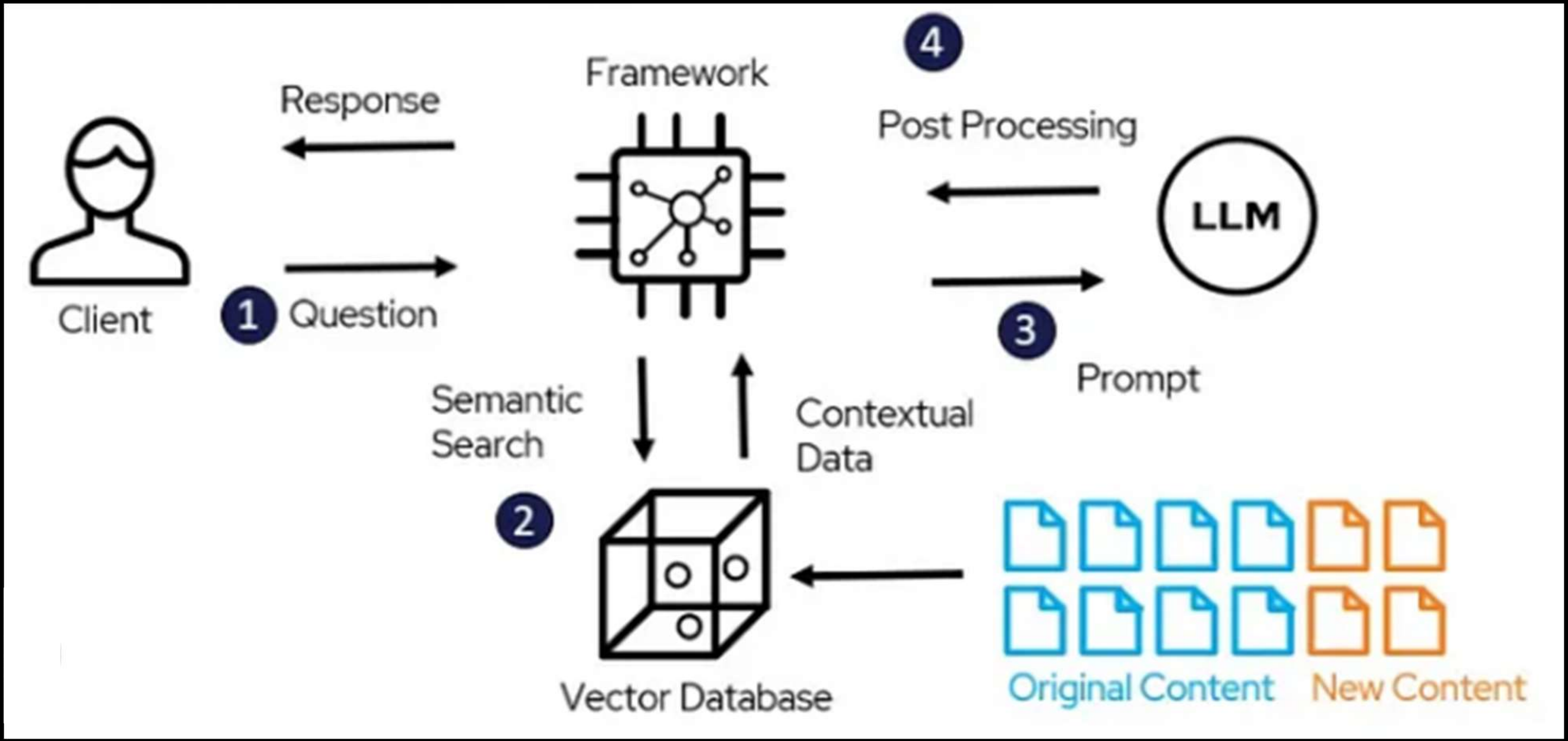
Embedding

This step involves converting text documents into numerical vectors. ML models are mathematical models and therefore require numerical data.

Storing

This step involves storing the embeddings vectors. Vectors are typically stored in Vector Databases which are best suited for searching.

Retrieval


Framework
Response
4
Post Processing
LLM
Client
1
Question
3
Prompt
Semantic Search
Contextual Data
2
Vector Database
Original Content
New Content

Popular Embedding Models

word2vec Google's Word2Vec is one of the most popular pre-trained word embeddings. The official paper - https://arxiv.org/pdf/1301.3781.pdf

GLOVE The 'Global Vectors' model is so termed because it captures statistics directly at a global level. The official paper - https://nlp.stanford.edu/pubs/glove.pdf

fastText Facebook's AI research, fastText builds embeddings composed of characters instead of words. The official paper - https://arxiv.org/pdf/1607.04606.pdf

Elmo Embeddings from Language Models, are learnt from the internal state of a bidirectional LSTM. The official paper - https://arxiv.org/pdf/1802.05365.pdf

BERT Bidirectional Encoder Representations from Transformers is a transformer bases approach. The official paper - https://arxiv.org/pdf/1810.04805.pdf

Popular Vector Databases

Faiss

Facebook AI Similarity search is a vector index released with a library in 2017

Pinecone

Pinecone is one of the most popular managed Vector DB for large scale

Weaviate

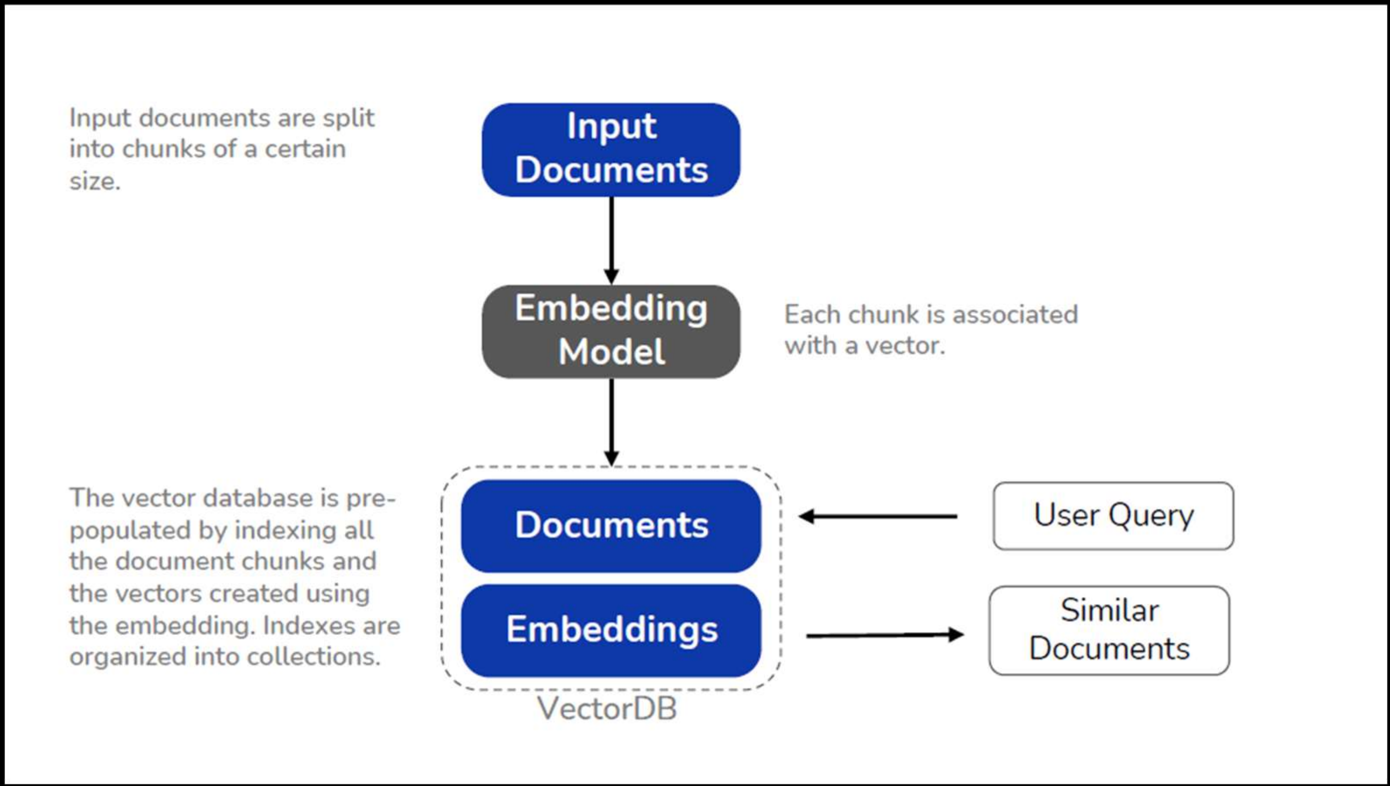
Weaviate is an open source vector database that stores both objects and vectors

Chroma

Chromadb is also an open source vector database.

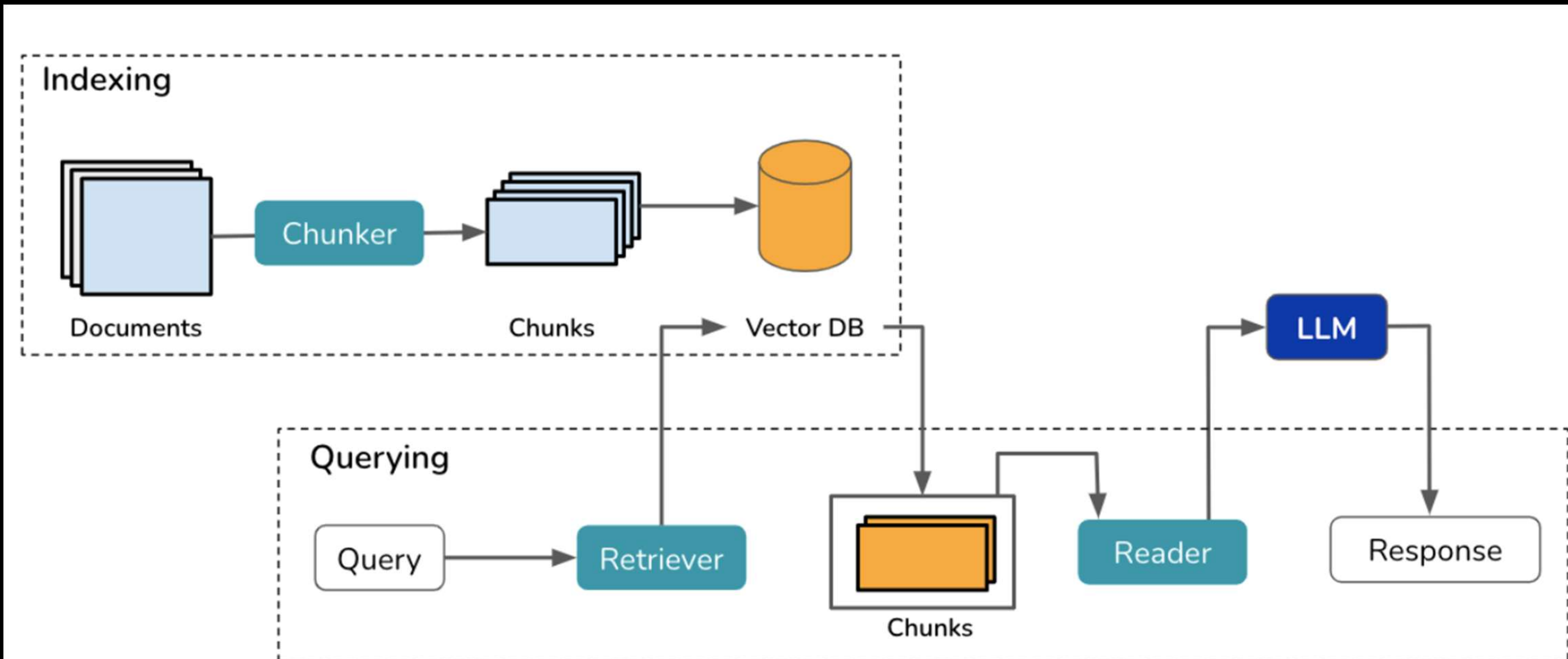
With the growth in demand for vector storage, it can be anticipated that all major database players will add the vector indexing capabilities to their offerings.

Vector database

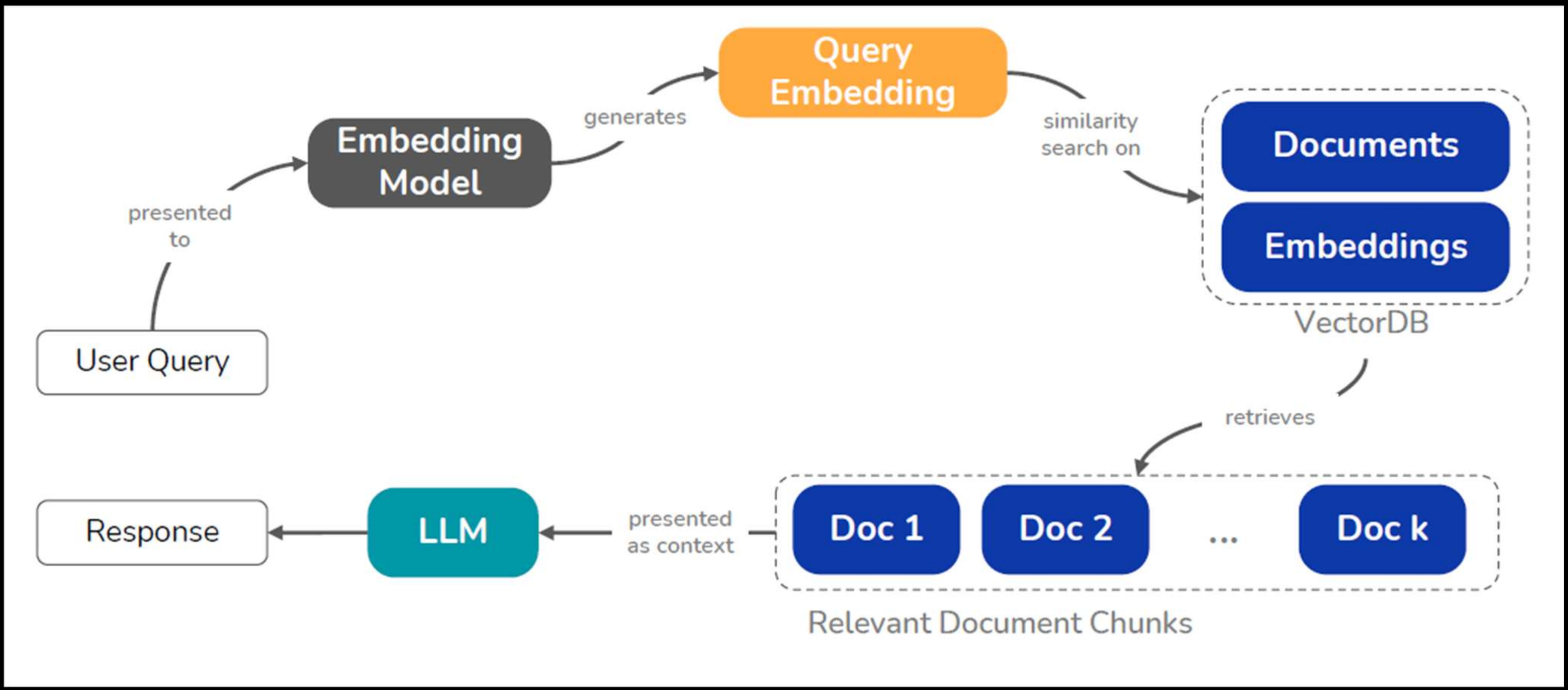


https://weaviate.io/blog/what-is-a-vector-database

RAG architecture in detail

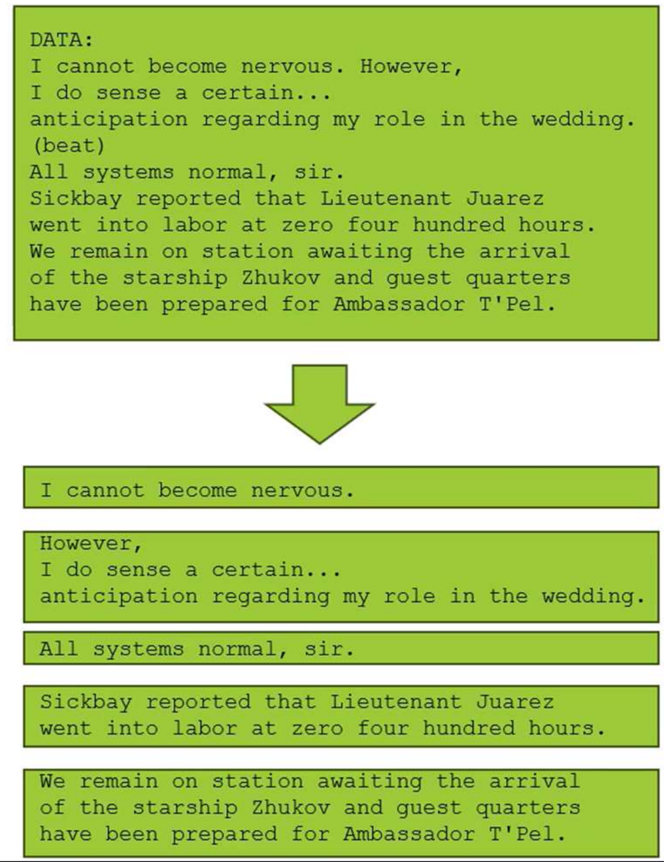


Retrieval and generation

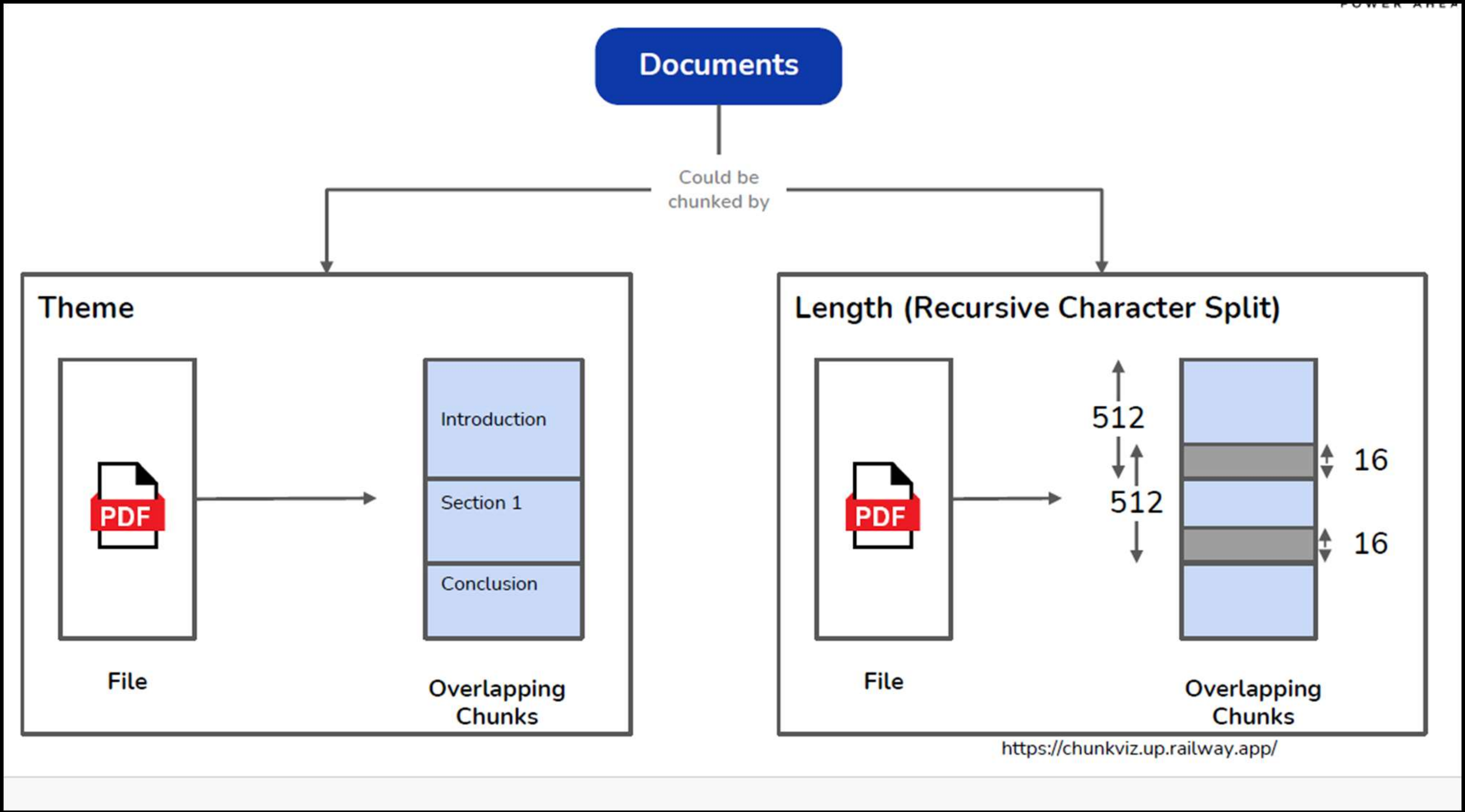


Chunking

- What should you be storing in your database?
- Data granularity matters
- Example: Every set of lines Data had, or individual sentences? Or blocks of text of a fixed length? Why just Data’s lines?
  - Or maybe summaries of those lines?
  - You can use an LLM for this too…
- The process of splitting up your data prior to storage is referred to as CHUNKING.



Chunking strategy



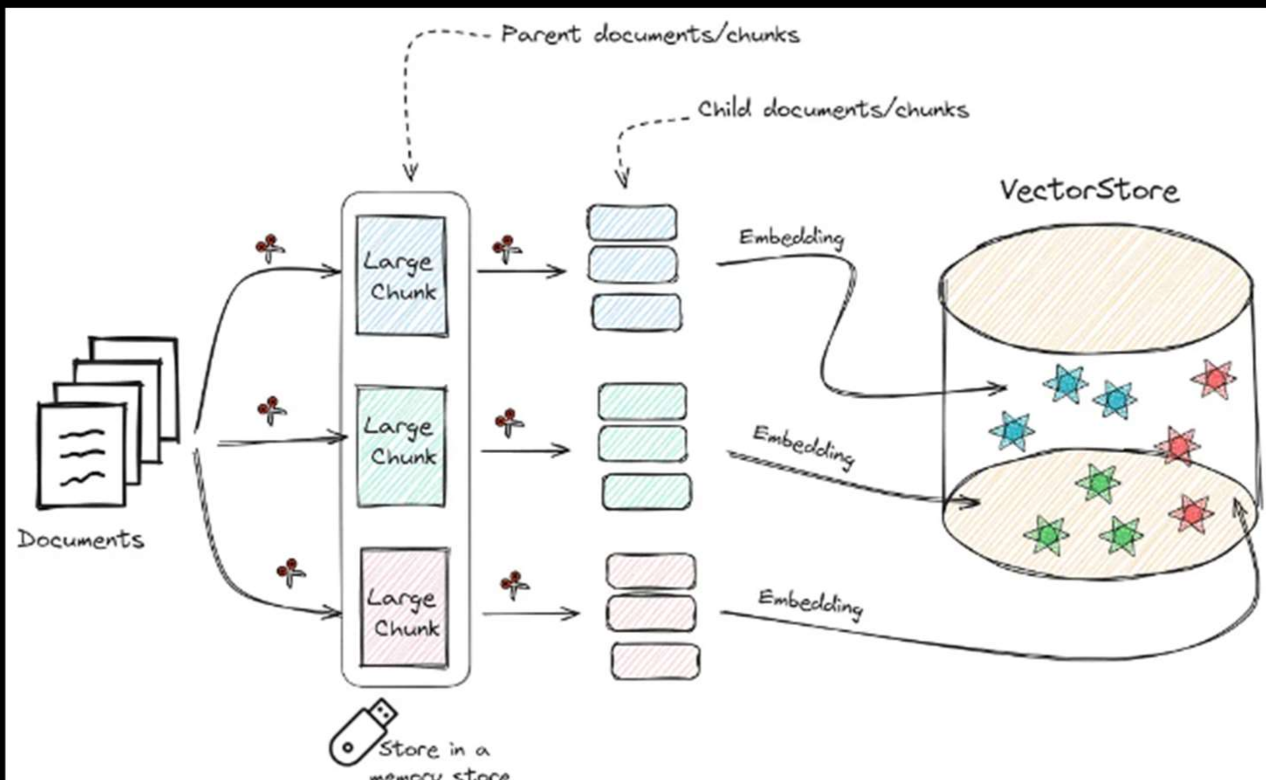
Chunking considerations

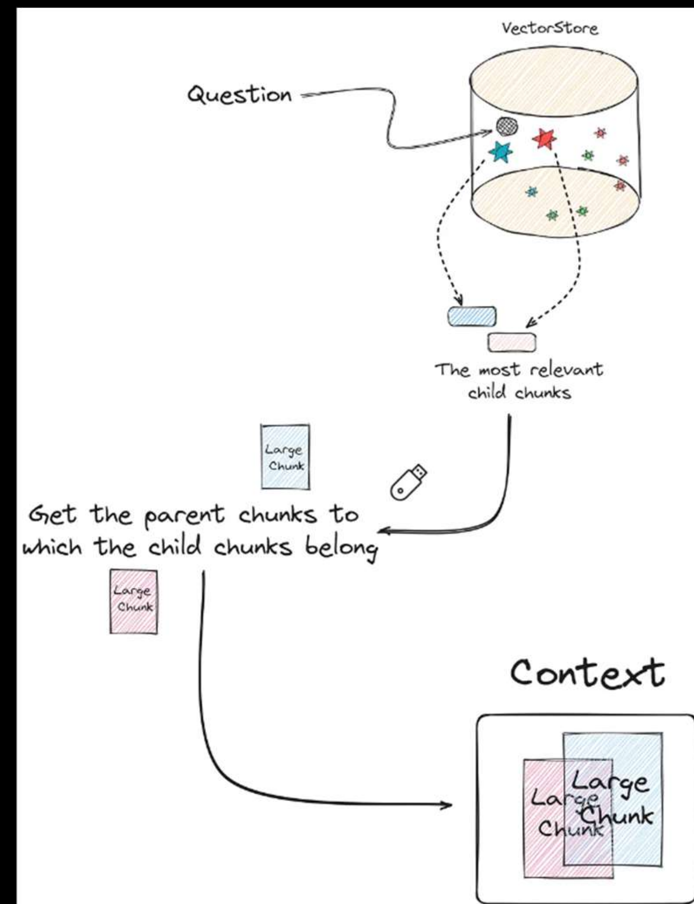
Chunk size

If we want to be precise in searching for the most relevant documents, we need to break our documents into **small chunks**.

But it is also very important to provide good context to the LLM, which is achieved by providing **larger chunks**.

Chunking – parent doc retriever





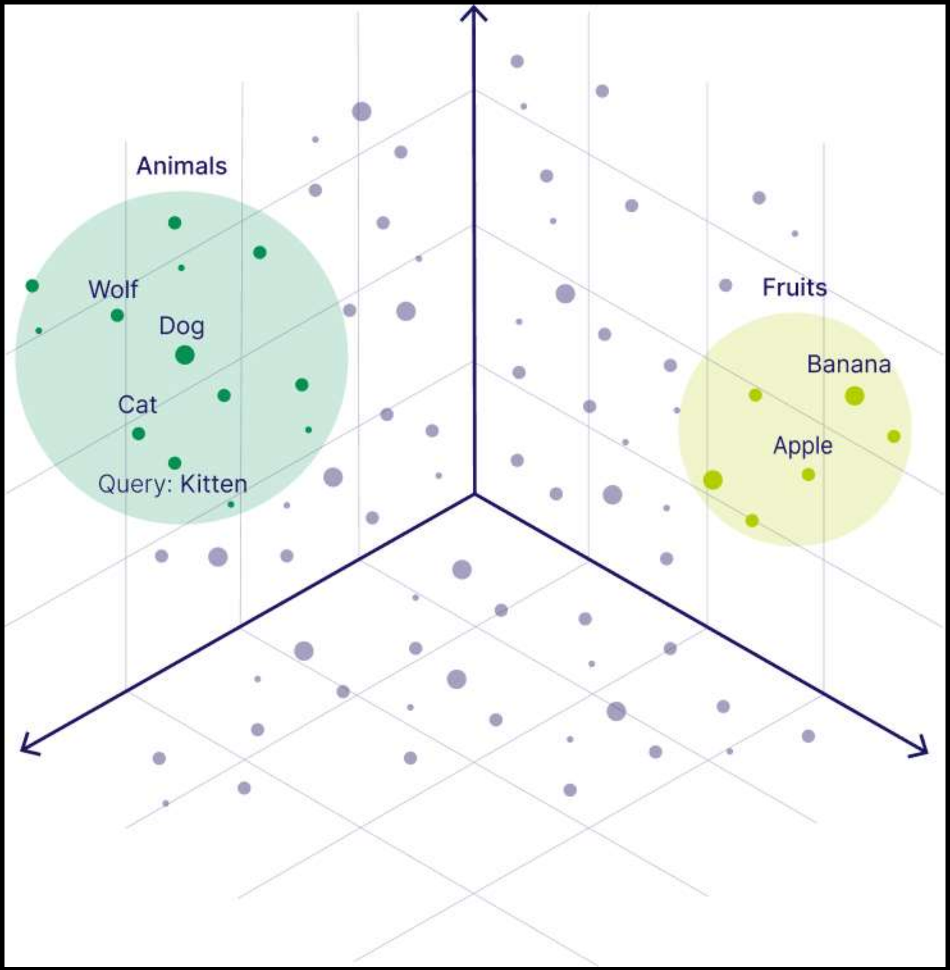
Embedding models

	Embedding model	Embedding size	Context size	Size (GB)	MTEB Rank (Feb 24)	Release date
2	e5-mistral-7b-instruct	4096	32768	14	4	04/01/2024
3	multilingual-e5-large-instruct	1024	514	1.12	10	08/02/2024
4	BGE-M3	1024	8192	2.27	NA	29/01/2024
5	nomic-embed-text-v1	768	8192	0.55	22	10/02/2024

Indexing

Hierarchical Navigable Small World (HNSW) algorithm

It is the default Approximate Nearest Neighbor (ANN) algorithm



RAG database

- You could just use whatever database is appropriate for the type of data you are retrieving
  - Graph database (i.e., Neo4j) for retrieving product recommendations or relationships between items
  - Elasticsearch or something for traditional text search (TF/IDF)
  - The functions / tools API can be used to try and get GPT to provide structured queries and extract info from the original query
    - “RAG with a Graph database” in the OpenAI Cookbook is one example
    - https://cookbook.openai.com/examples/rag_with_graph_db
- But for some reason, most examples you find of RAG use a Vector database

```
Q: 'Which pink items are suitable
for children?'
{
  "color": "pink",
  "age_group": "children"
}

Q: 'Help me find gardening gear
that is waterproof'
{
  "category": "gardening gear",
  "characteristic": "waterproof"
}

Q: 'I'm looking for a bench with
dimensions 100x50 for my living
room'
{
  "measurement": "100x50",
  "category": "home decoration"
```

Vector database – how it works?

Let's say you want to search for photos from your vacation,

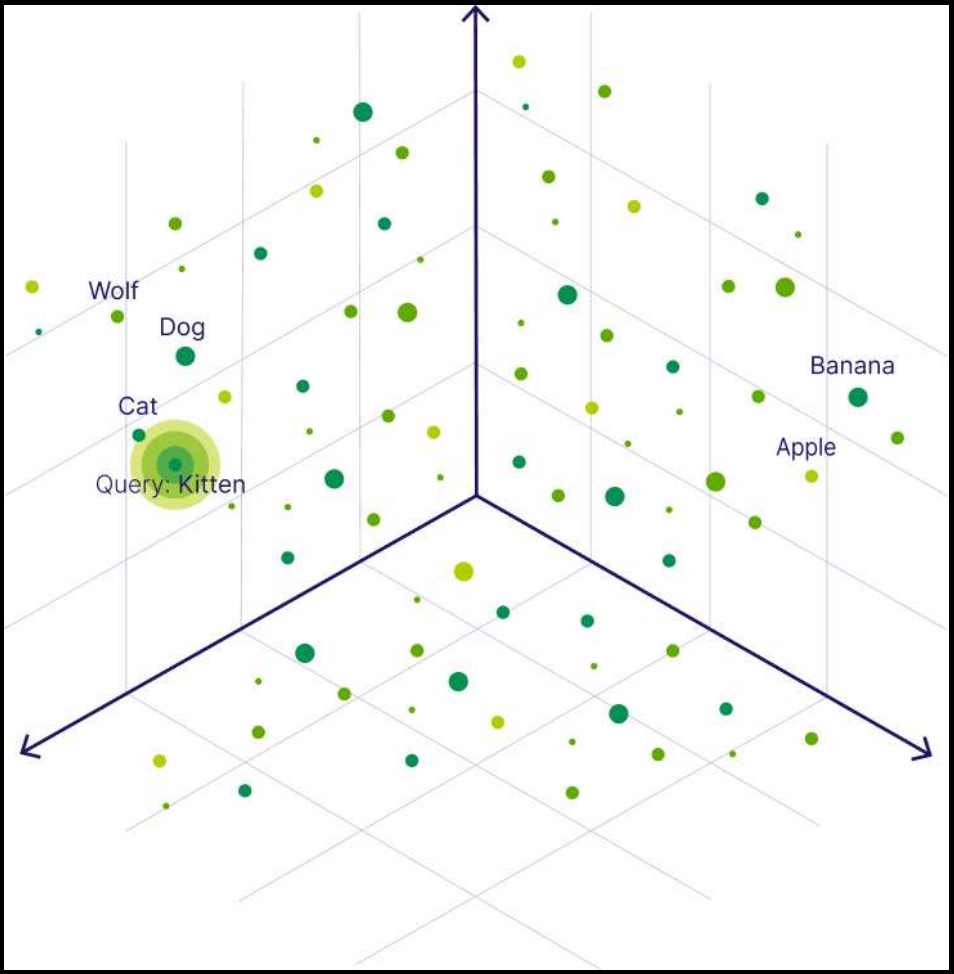
So you type “family vacation in Prague” into the input,

A vector database would turn that text query into a vector and then search for the object vectors **in closest proximity** to the query vector.

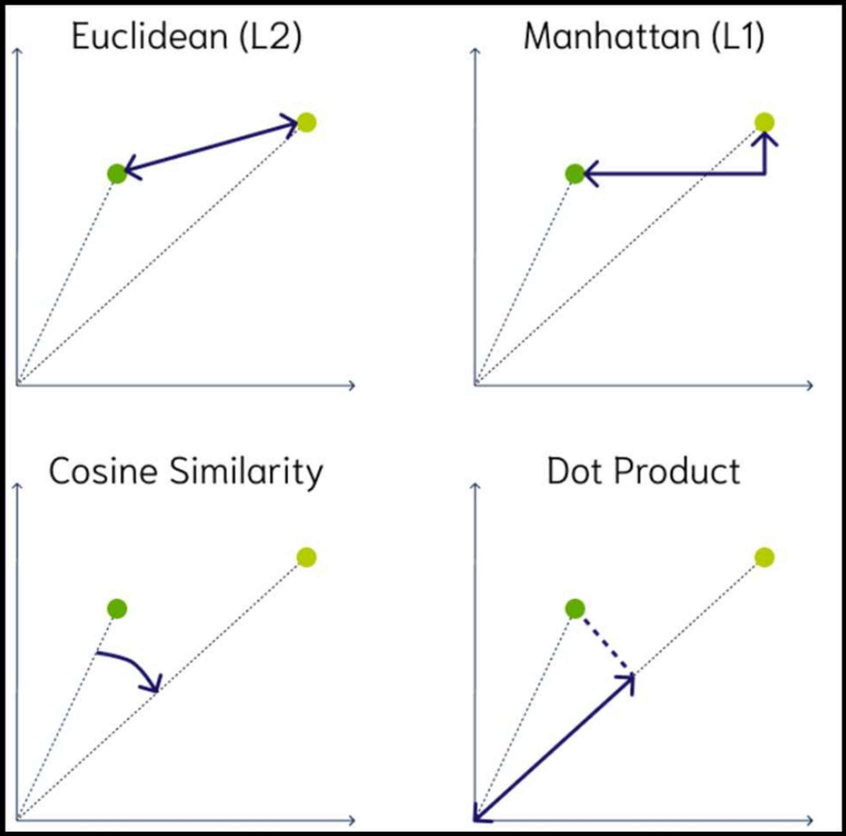
These could be text documents describing the vacation or even pictures you took, and those files are then returned to you.

Search and retrieval

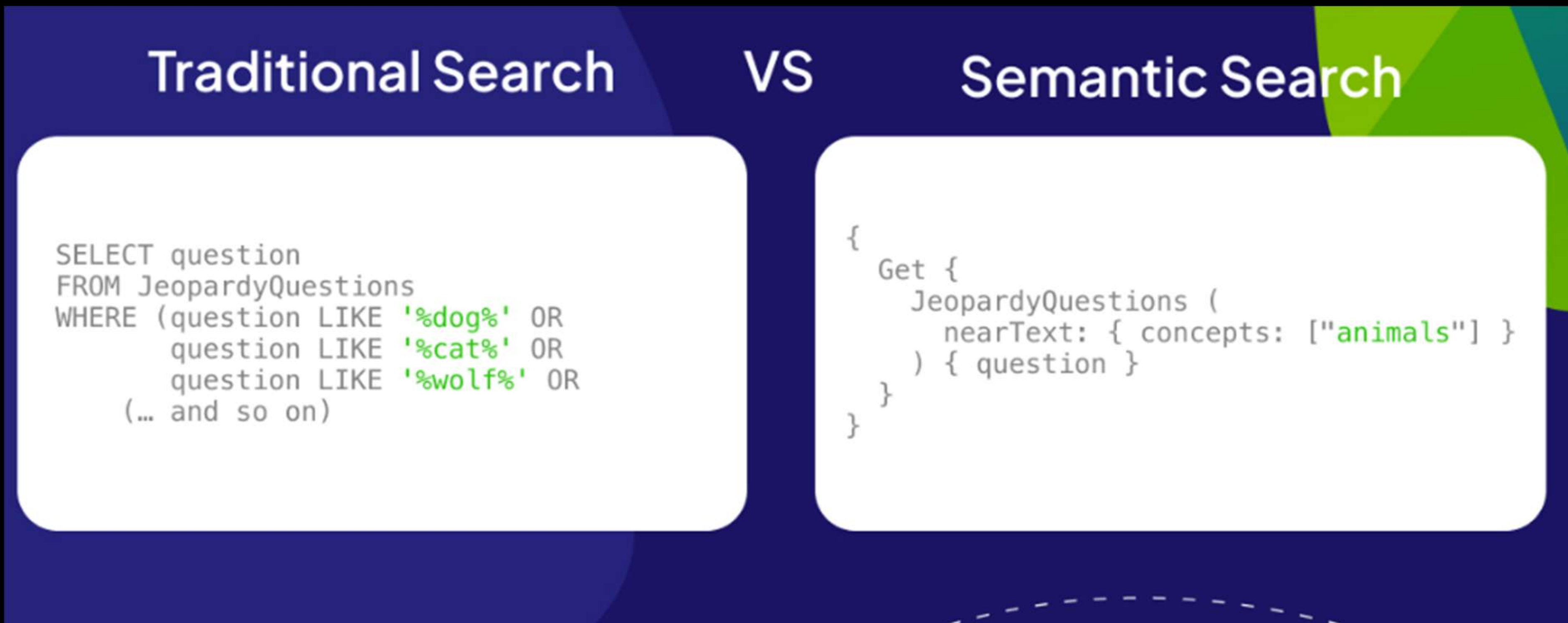
Semantic Search



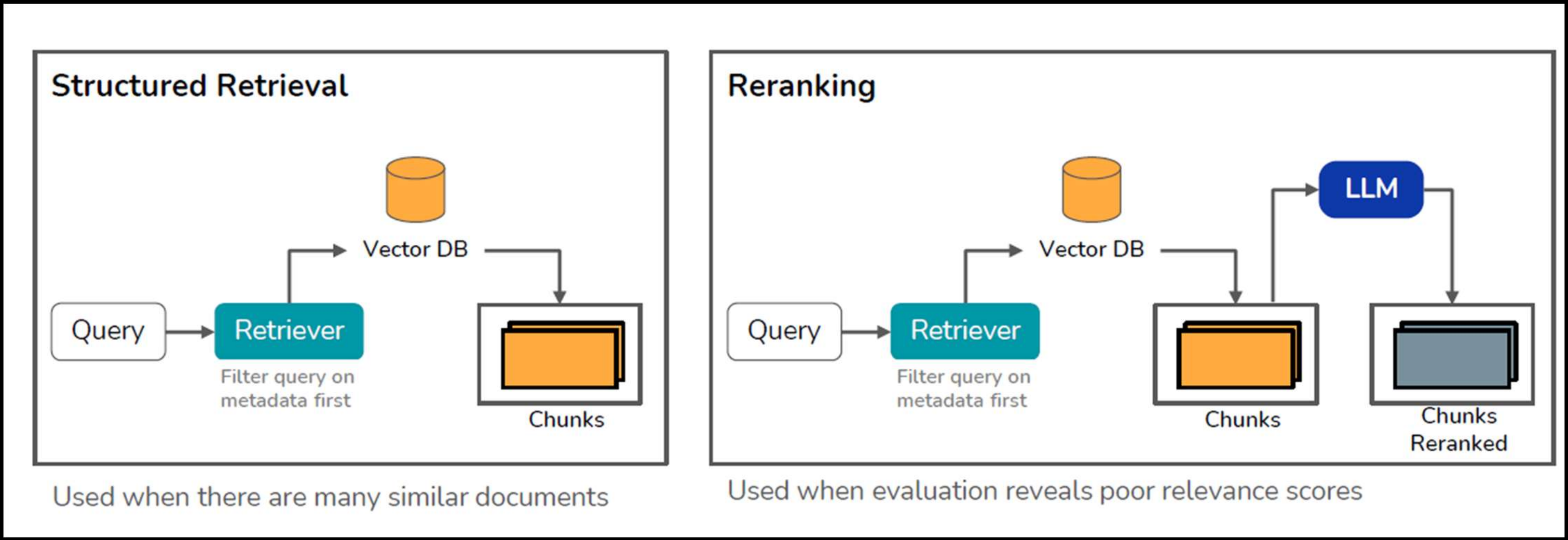
Distance measurement



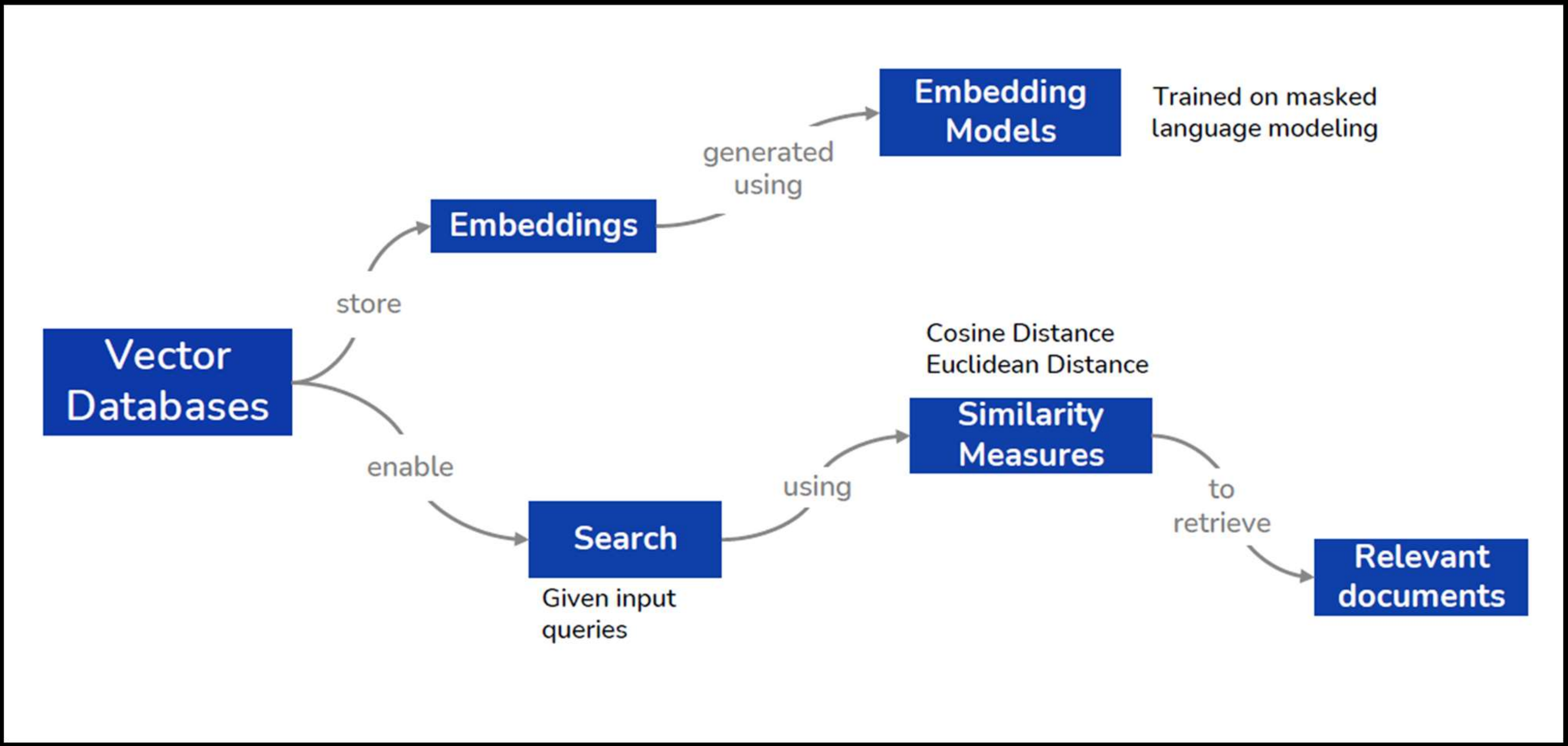
Traditional search Vs semantic search



Retrieval techniques



Vector database – summary of actions



Adding metadata – support citations

- **Step A**: You chunk `doc1.pdf` and `doc2.pdf`, store chunks with `metadata={"source": "doc1.pdf", "page": 2}`, etc.
- **Step B**: When the user asks a question, you embed it, get top-k chunks from the vector store.
- **Step C**: The store returns chunk texts + metadata.

User query:

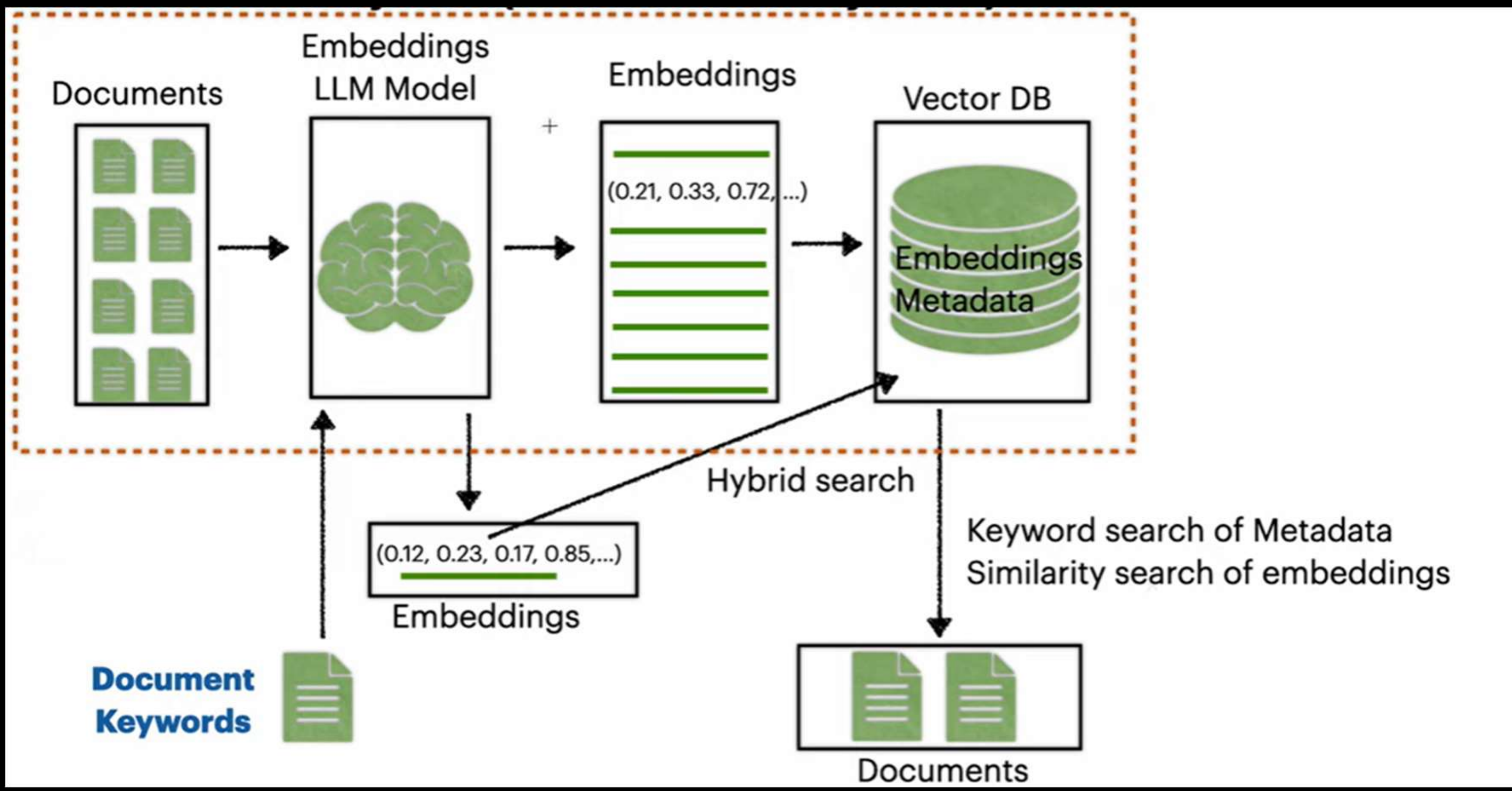
“give me the pricing details for solar panels”

Retrieved Context:

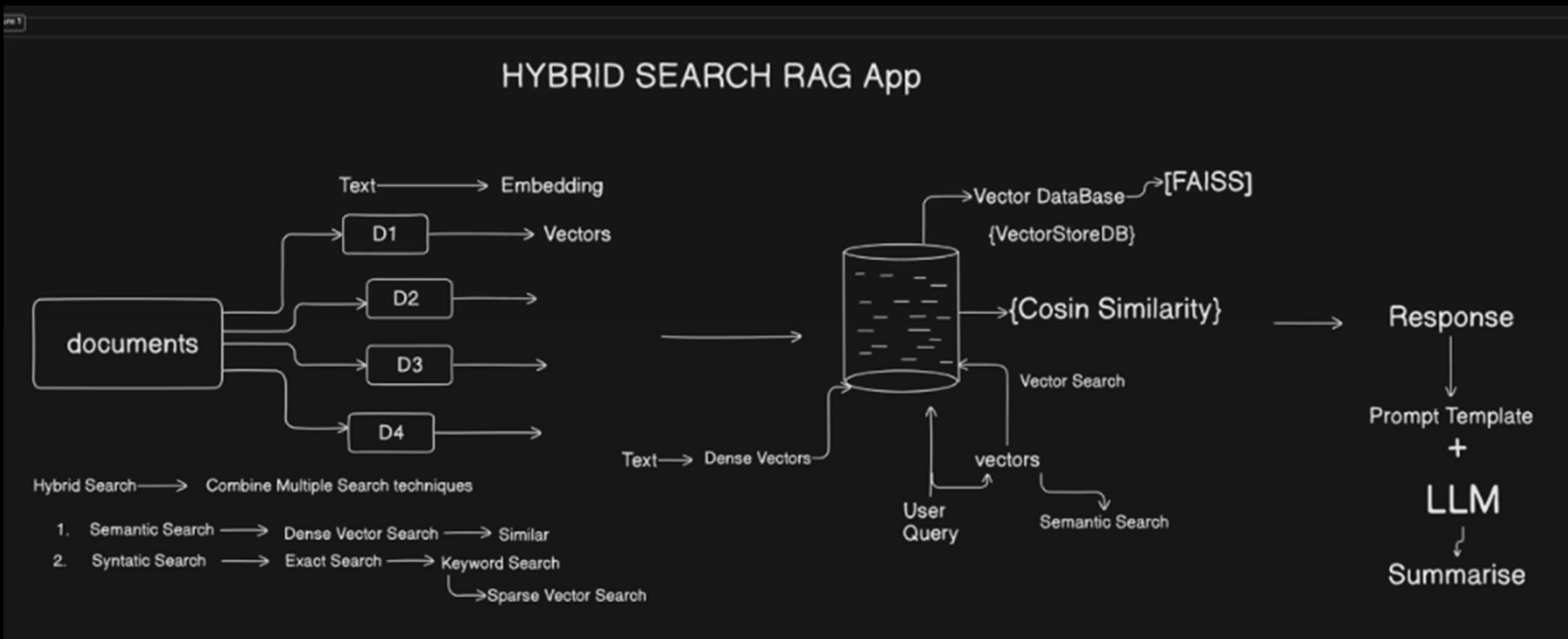
1) Source: doc1.pdf, Page: 5 "Solar panels cost around $X per watt...“
2) Source: doc2.pdf, Page: 3 "Rebates are available in certain states..."

Hybrid Search

Combine Syntactic/keyword search and semantic search

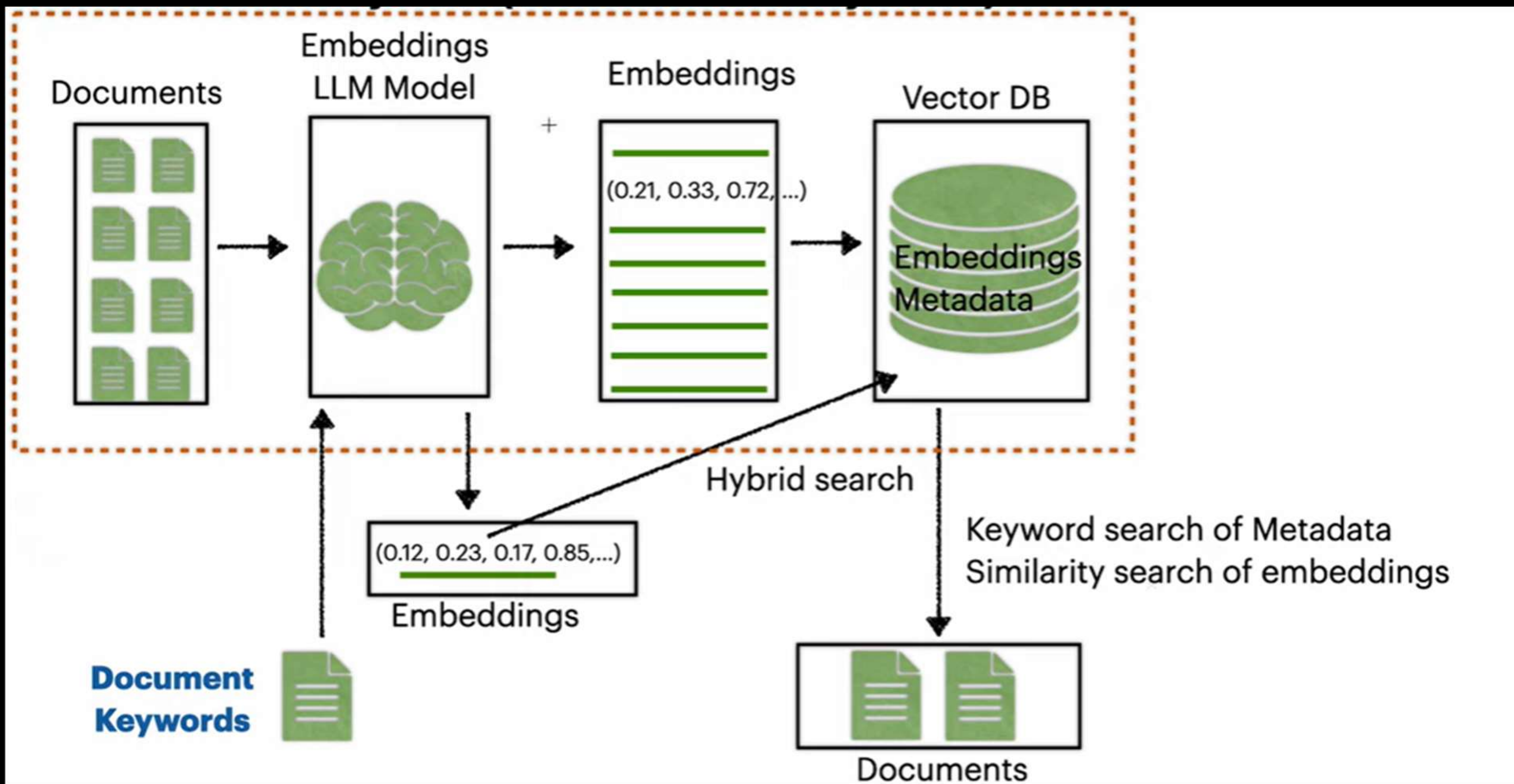


Hybrid Search

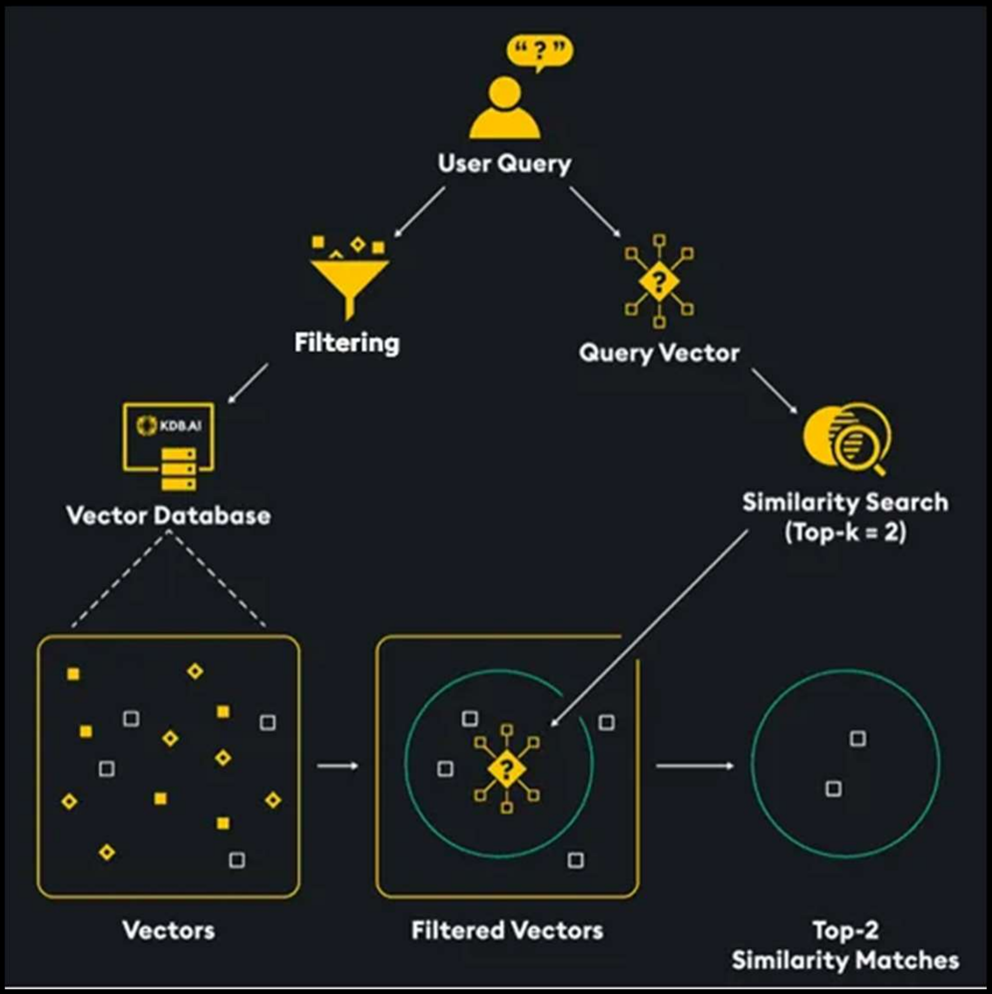


Hybrid Search

Metadata, keywords searched using syntactic search

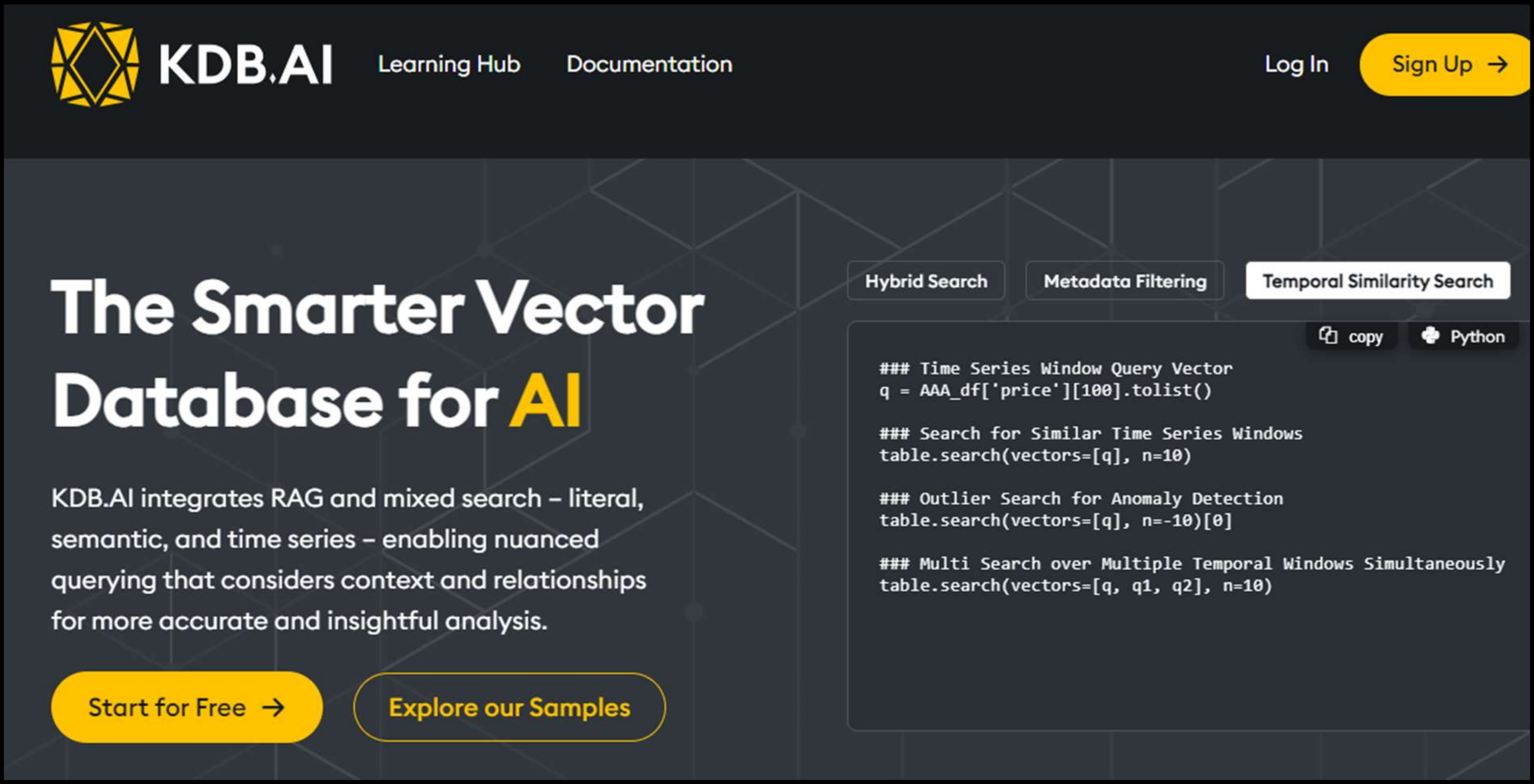


Retrieval optimization - Metadata filtering



Metadata examples include
Dates
Times
Genres
Categories
Names
Types
Descriptions
Etc.

Specialized vector databases



https://kdb.ai/

Metadata filtering

Let’s imagine that we have stored in our vector database a large number of experiences and leisure offers (Ex: surf classes, zip line, gastronomic route, etc.).

The description of the experience is what we have encoded, using our embedding model.

Additionally, each offer has 3 key values or metadata: Date, price and place.

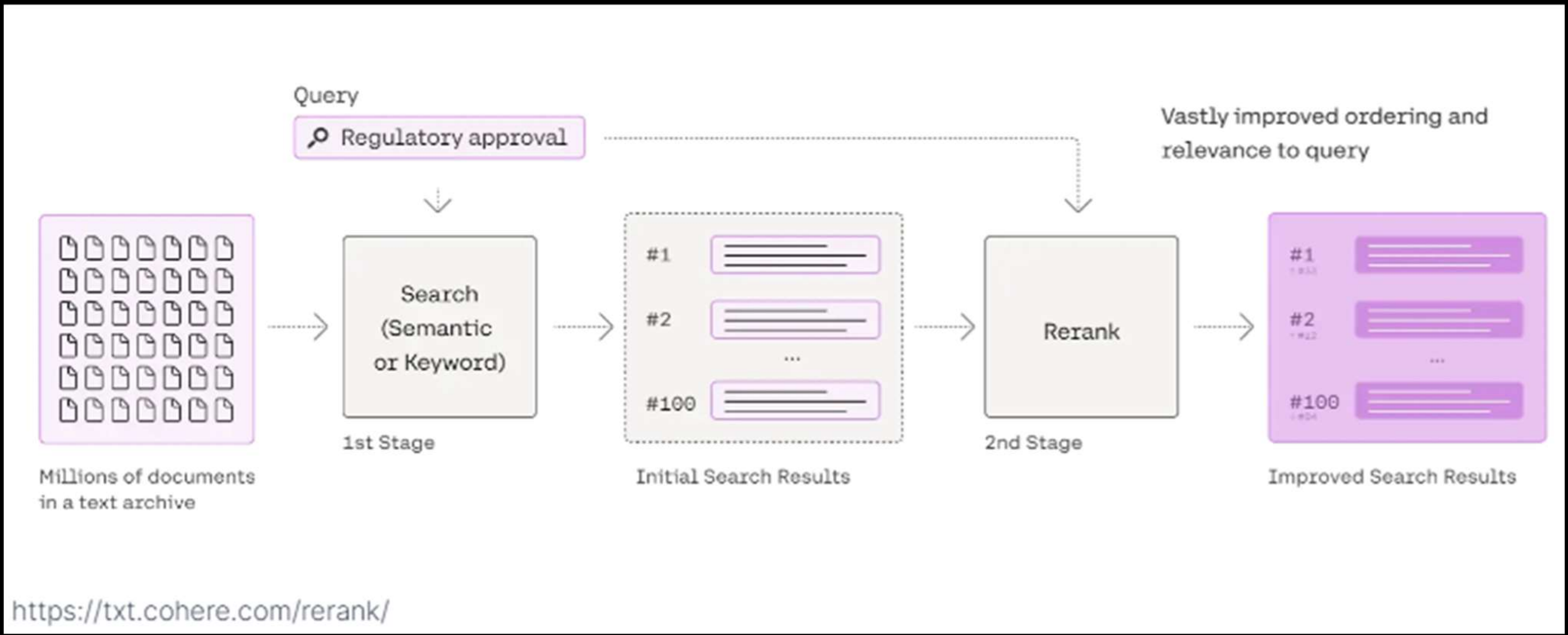
Let’s imagine that a user is looking for an experience of this style: An experience in nature, that is for the whole family and safe. Furthermore, the price must be less than $50 and the place is California.

Example of metadata filtering

```
#Search query specifying the query vector, top-k=3, and metadata filters
table.search(
  query_vector,
  n=3,
  filter=[("like", "Director", "George Lucas"),("=", "ReleaseYear", "1977")]
)
```

The filtering greatly optimizes both the accuracy and efficiency of the similarity search, especially at scale.

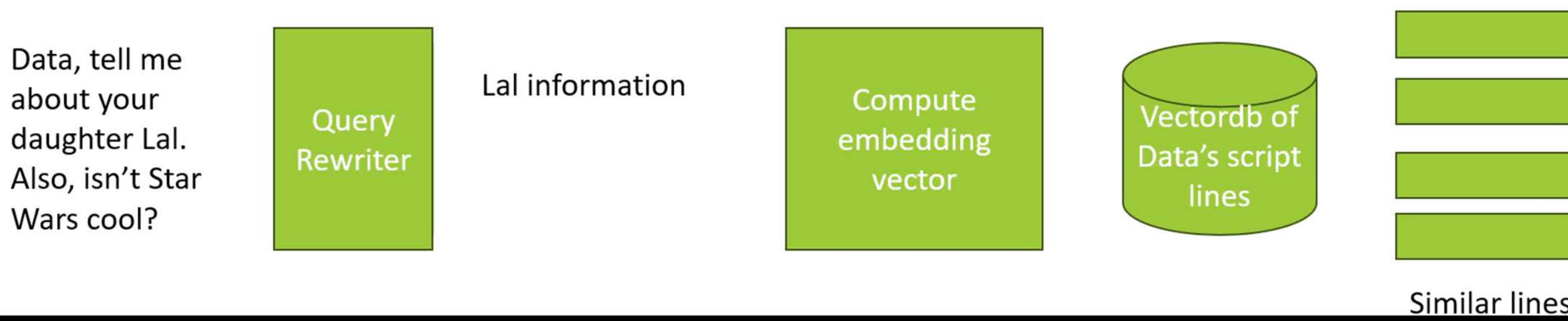
Re-ranking



[advanced-rag-techniques/reranking.py at main · pdichone/advanced-rag-techniques · GitHub]()

Query re-writing

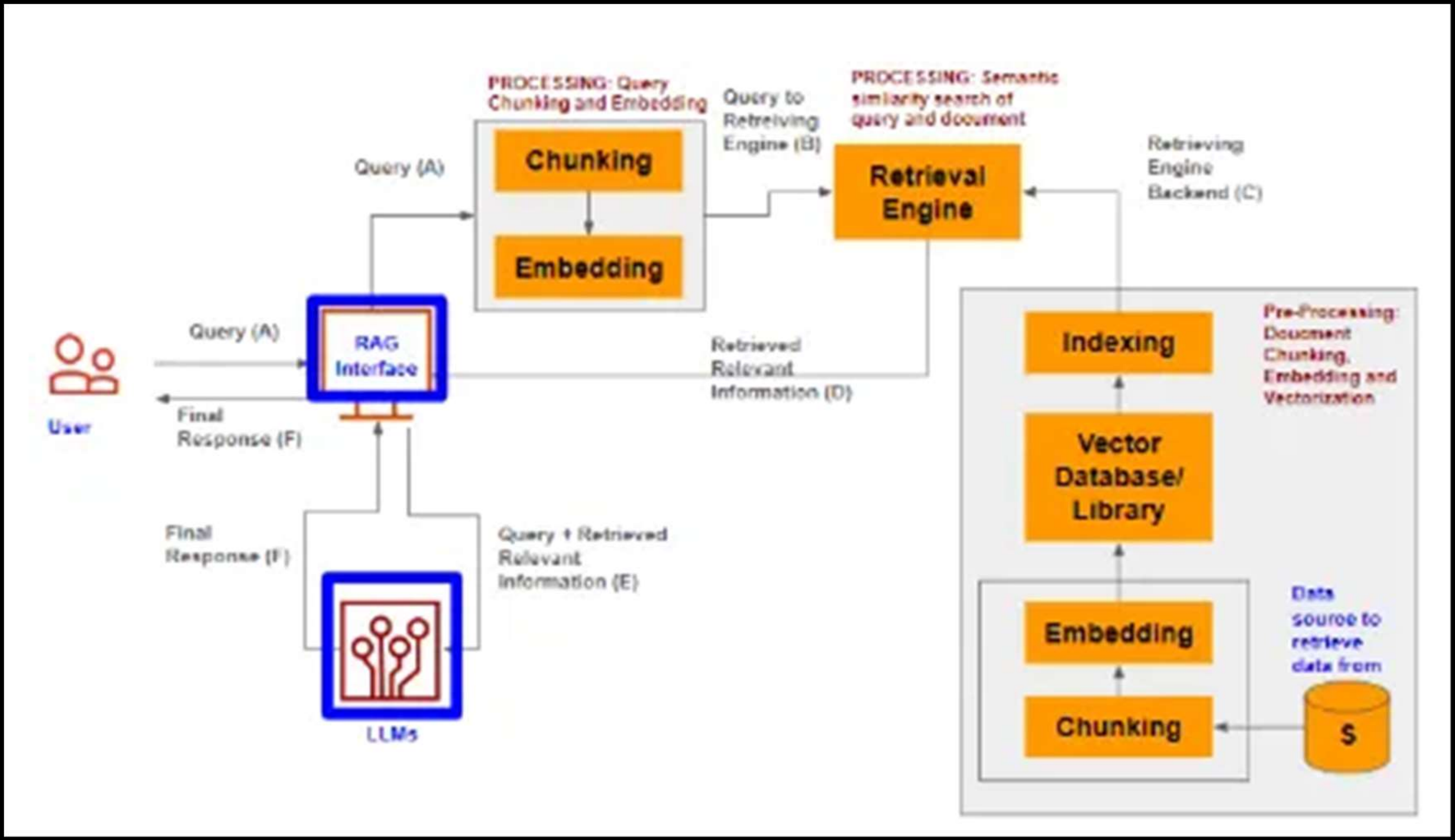
- A query that mixes different semantic meanings won't yield a good semantic search result in a vector DB.



Query re-writing

- Contextual Compression — Retrieval mechanism
- MultiQueryRetriever mechanism
- MultiVector Retriever Mechanism
- Time-weighted vector store retriever
  (gives weightage to the time the document was accessed)
- Recursive or Iterative Retrieval
- Summary based retrieval
- Rule based retrieval
- Ensemble retriever

What steps can be tuned?



RAG Optimization knobs

Chunking
Semantic chunking
Agentic chunking

Indexing
vector compression
Metadata
Hyperparameter tuning
Choose right ANN algo

Query optimization
Prompt engineering
Query transformation, splitting
Query expansion, compression
Query routing, augmentation
Lost in the middle problem

Retrieval knobs
Embedding models
hybrid search weighting
re-ranker models
Multi-index search configurations
Metadata filtering.
Time-weighted retrieving
Summary based retrieval
Ensemble retriever

Generation knobs
Choice of LLM
LLM configuration & Tuning
(PEFT, FFT)

RAG pros and cons

- Faster & cheaper way to incorporate new or proprietary information into "GenAI" vs fine-tuning
- Updating info is just a matter of updating a database
- Can prevent "hallucinations" when you ask the model about something it wasn't trained on
- If your boss wants "AI search", this is an easy way to deliver it.
- Technically you aren't "training" a model with this data

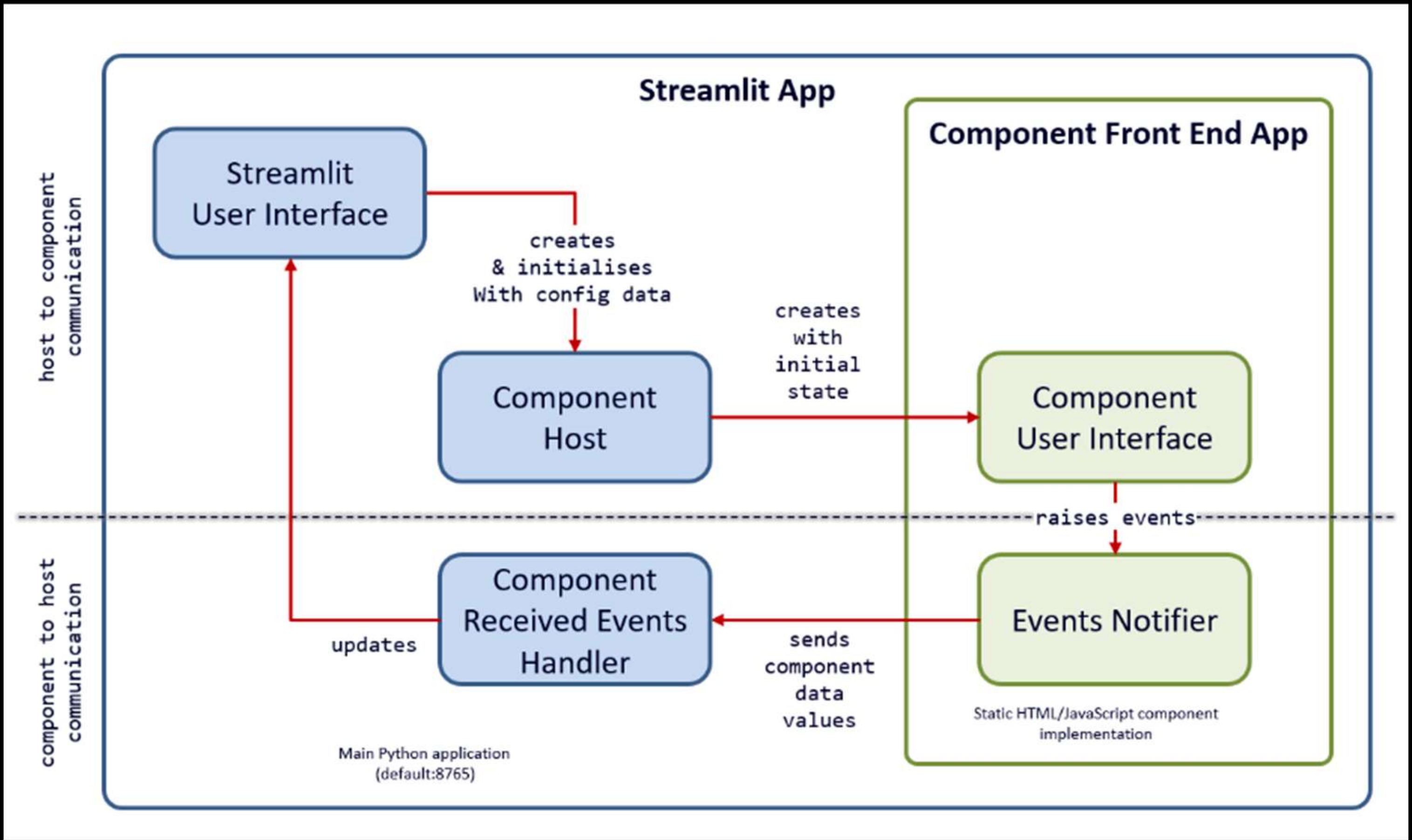
- You have made the world's most overcomplicated search engine
- Very sensitive to the prompt templates you use to incorporate your data
- Non-deterministic
- It can still hallucinate
- Very sensitive to the relevancy of the information you retrieve

RAG hands-on

Streamlit

- Open-source app framework that helps create beautiful data apps in hours using pure python
- Acquired by Snowflake in 2022 for USD800M
- Aligns well with chatbot/chat based interfaces and integration with LLMs
- Well integrated and supported by popular frameworks and platforms such as Langchain, Huggingface etc.

Streamlit



Streamlit App
Component Front End App
host to component communication
component to host communication
Streamlit User Interface
creates & initialises With config data
Component Host
creates with initial state
Component User Interface
raises events
Component Received Events Handler
updates
sends component data values
Events Notifier
Static HTML/JavaScript component implementation
Main Python application (default:8765)

PDF chatbot with streamlit and Azure OpenAI