Week 4: Embedding Models and Advanced Queries

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Class Overview

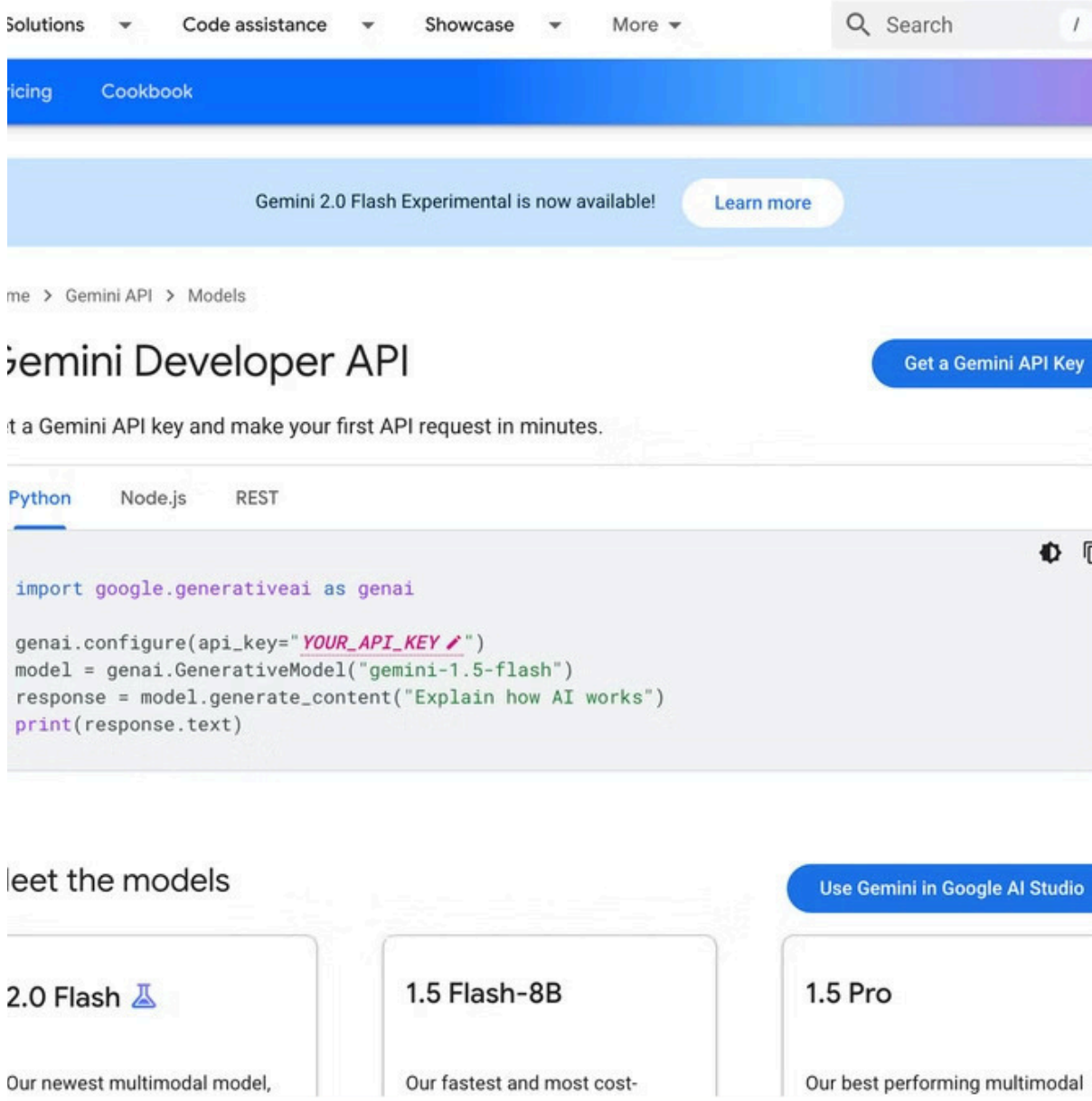
- **Goals for Today**:
  - Setting up Gemini
  - Introduction to:
    - Vector Embedding
    - Embedding Models
    - Vector Database
    - Basics of RAG
  - Usage throttling and API limits
- **Prerequisite Knowledge**:
  - Basic prompt engineering, token counting, and model parameters

Recap of Previous Lessons

- **Prompt Engineering**: Techniques to craft effective prompts.
- **Token Counting**: Understanding token limits for efficient querying.
- **Model Parameters**: Key parameters like temperature, max tokens, and top_p.
- **Importance of Understanding API Limits**: Helps avoid unnecessary costs or throttling issues.

Setting Up Gemini - Quick Review

- **Setting up API Keys**:
  - Navigate to [Gemini API Docs] for setup guide.
- **Environment Configuration**:
  - Install necessary packages (e.g., gemini-client, openai, etc.).
  - Set up authentication.
- **Usage Throttling**:
  - **Rate Limiting**: Requests per minute/hour.
  - **Practical Tips**: Set usage limits for small projects in the Gemini dashboard.

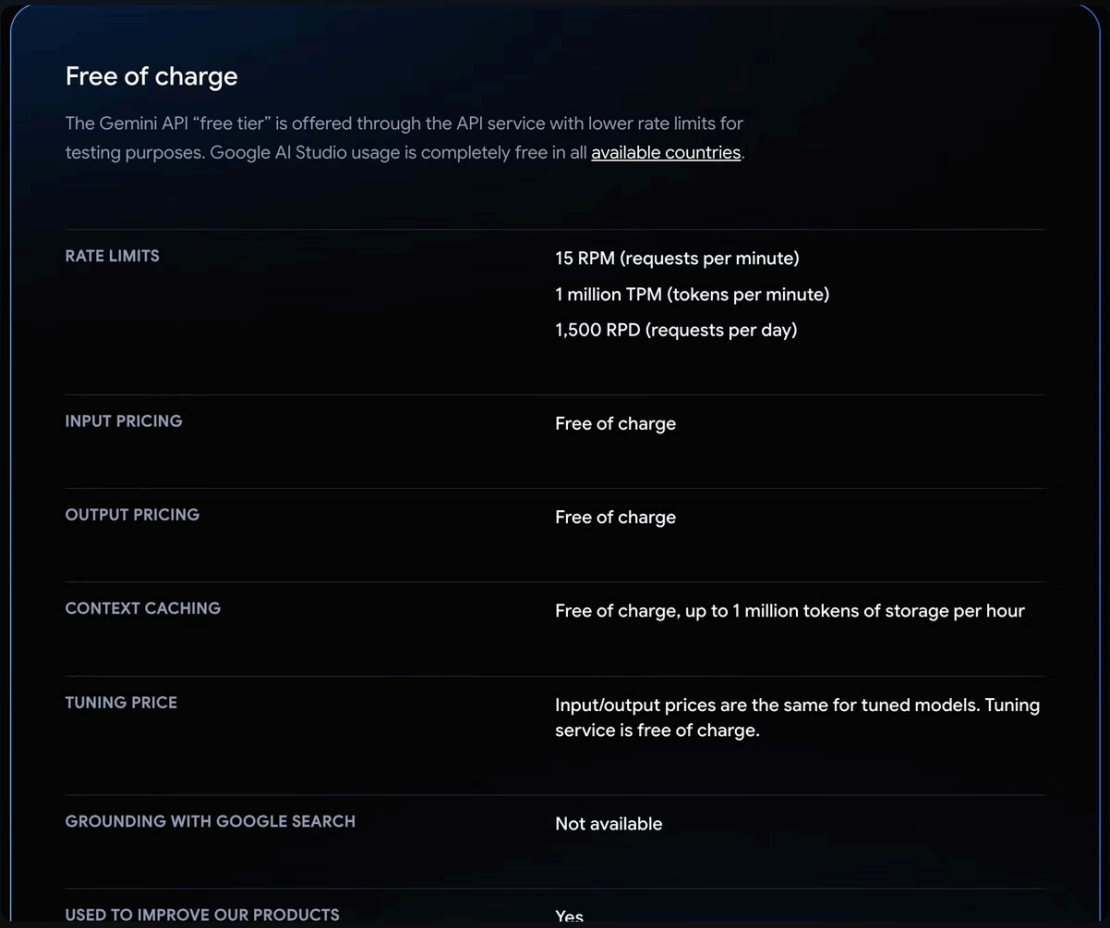


Introduction to Embedding Models

- **What Are Embeddings?**
  - A technique to represent text data as high-dimensional vectors.
  - Captures semantic meaning, unlike simple keyword-based methods.
  - Most LLMs (GPT, Gemini, LLAMA) have their respective embedding models
- **How Do They Work?**
  - We throw a lot of text data into a model.
  - The model looks at which words tend to show up together in similar contexts.
  - Over time, it learns to represent words as vectors (points) in a space where similar meanings are grouped together.
  - These vectors reflect the semantic relationships between words based on how they are used in real-world data.
- **Why Do We Use them?**
  - Allows search without exact phrase
  - Provides insight into datas

Usage Throttling Explained

- **What is Throttling?**:
  - Manage load and avoid service interruptions.
  - Key settings in Gemini's setup for managing your request frequency.
- **When to Use Throttling**:
  - Avoid high costs with excessive requests.
  - Improve system reliability for personal or production projects.
- **Do you need to be concerned?**
  - For this class, [not really]

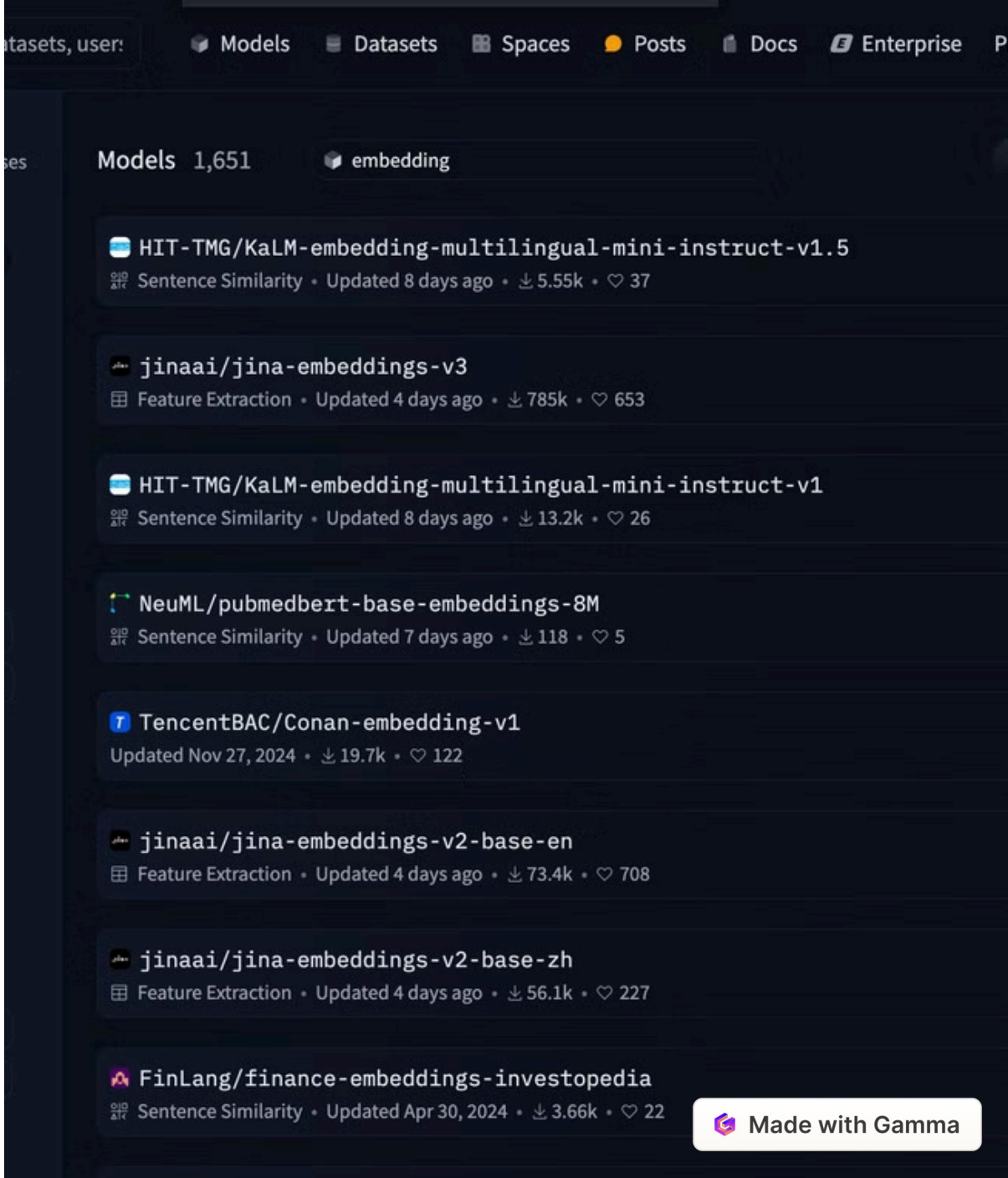


Embeddings vs. Text Generation

- **Text Generation Models**:
  - Generate content based on input prompts.
  - Example: ChatGPT, GPT-4.
- **Embedding Models**:
  - Encode text into vectors that can be compared for similarity.
  - Example: Sentence-BERT, OpenAI Embedding API.

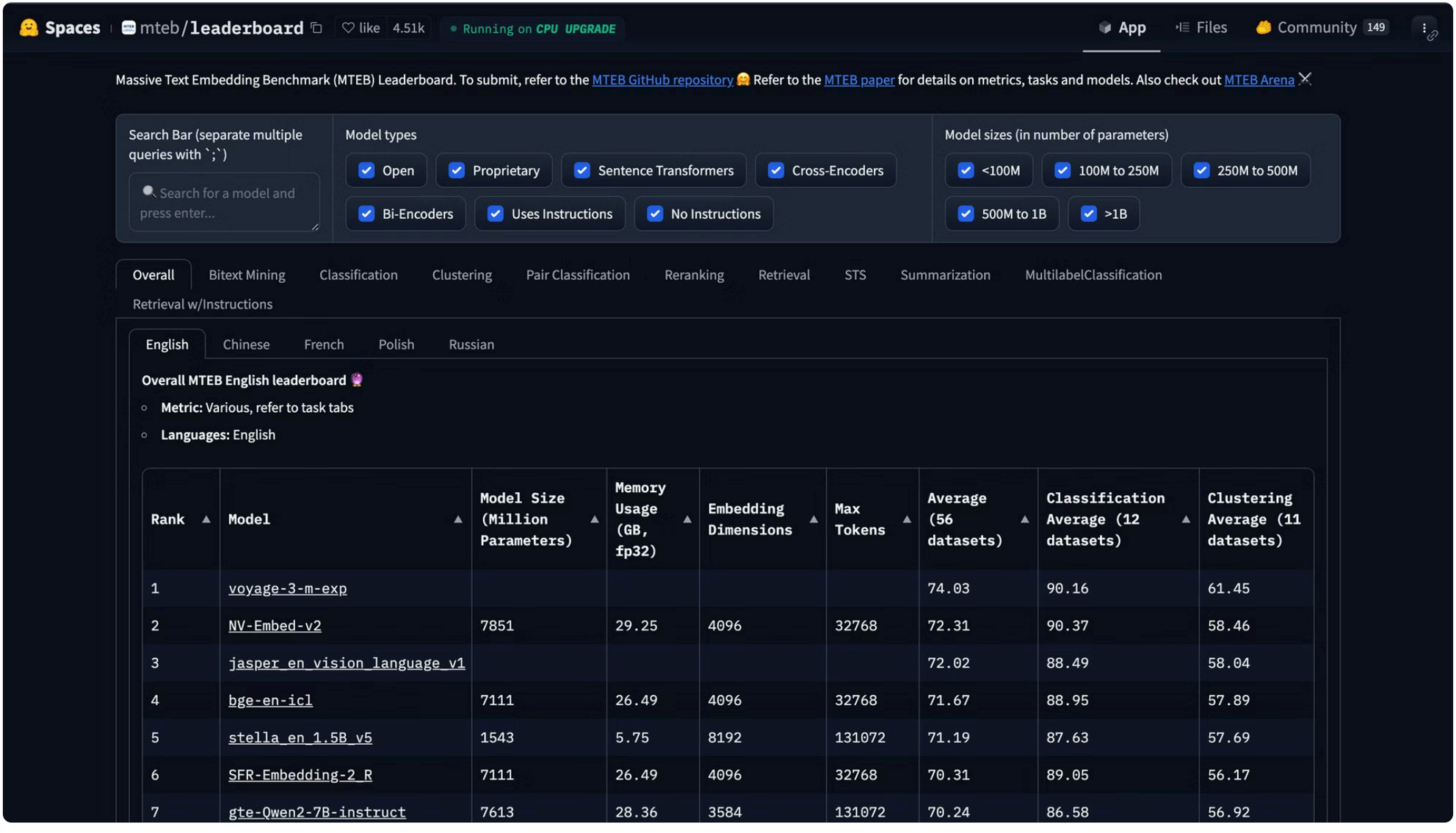
Example Embedding Models:

- [OpenAI Embedding Docs]: text-embedding-3-small/large
- [Google Embeddings]: text-embedding-005
- [Sentence-BERT GitHub]
- [Many more open source options on Hugging face]



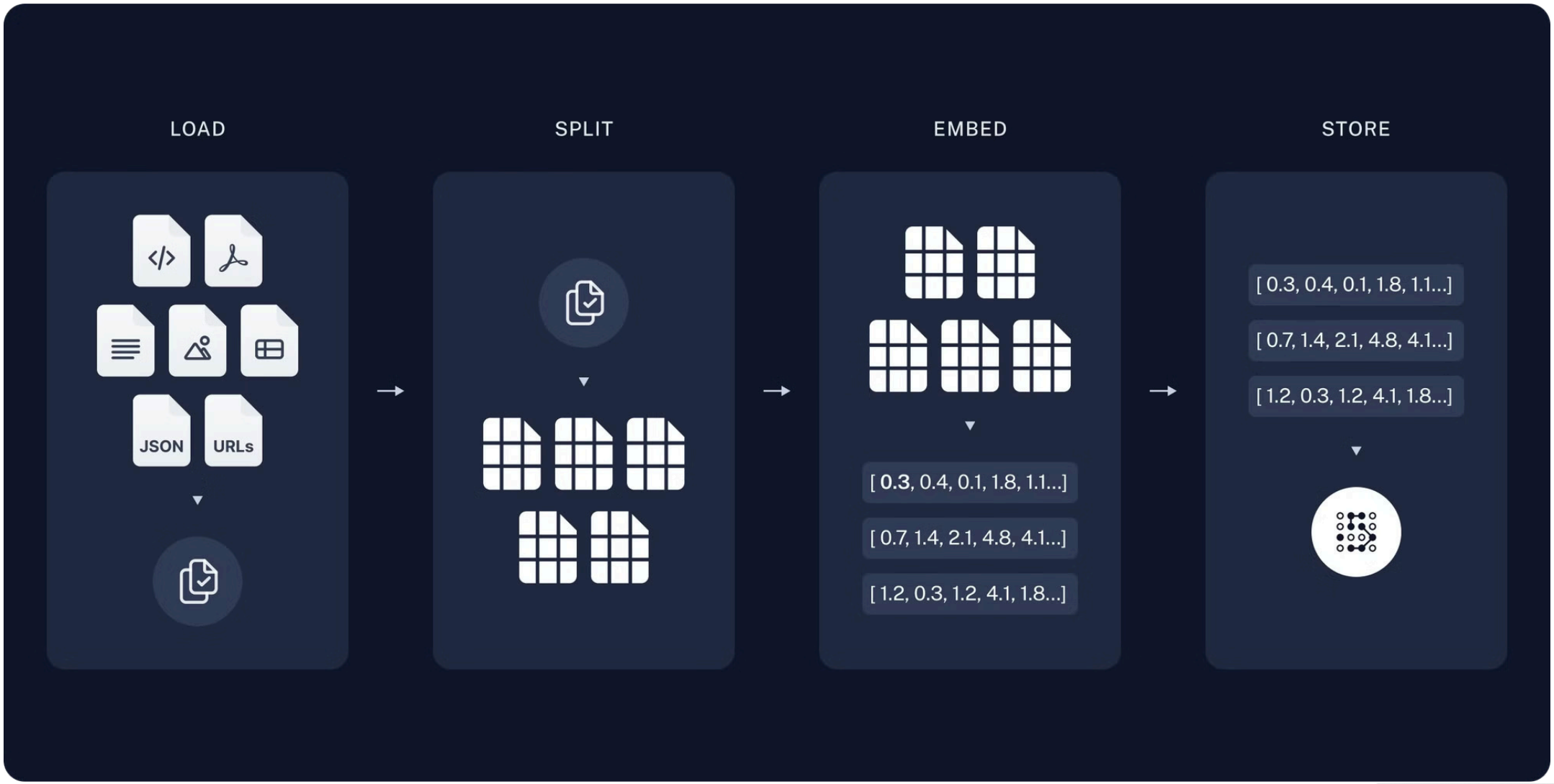
Why do we care which model is used?

- [Just like LLMs, Embedding models are different]



Rank	Model	Model Size (Million Parameters)	Memory Usage (GB, fp32)	Embedding Dimensions	Max Tokens	Average (56 datasets)	Classification Average (12 datasets)	Clustering Average (11 datasets)
1	voyage-3-m-exp					74.03	90.16	61.45
2	NV-Embed-v2	7851	29.25	4096	32768	72.31	90.37	58.46
3	jasper_en_vision_language_v1					72.02	88.49	58.04
4	bge-en-icl	7111	26.49	4096	32768	71.67	88.95	57.89
5	stella_en_1.5B_v5	1543	5.75	8192	131072	71.19	87.63	57.69
6	SFR-Embedding-2_R	7111	26.49	4096	32768	70.31	89.05	56.17
7	gte-Qwen2-7B-instruct	7613	28.36	3584	131072	70.24	86.58	56.92

Embed workflow



What does the code look like

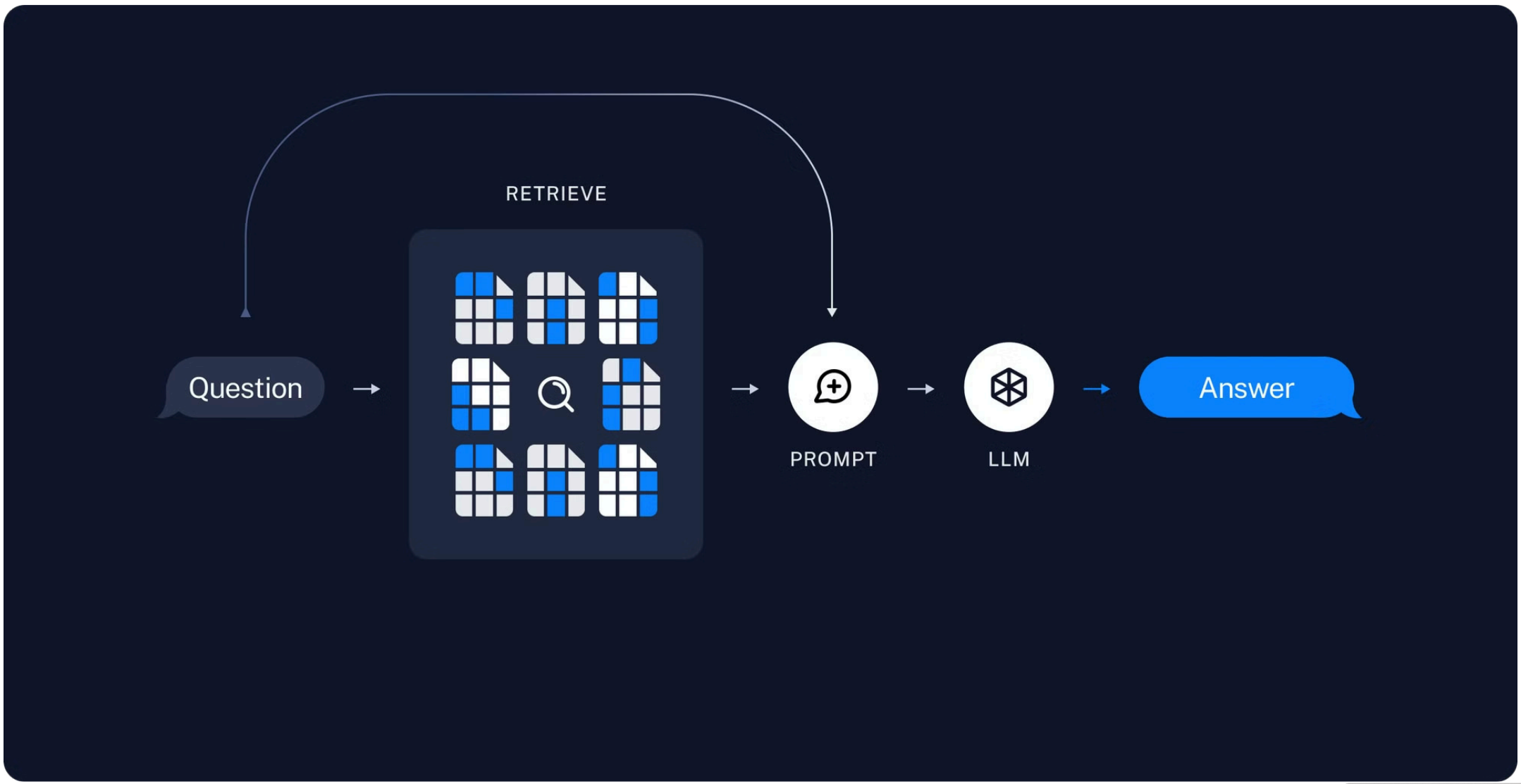
- **Step 1: Prepare Data**
  - Collect a set of documents
- **Step 2: Generate Embeddings**
  - Embed the entire dataset.
- **Step 3: Query Processing**
  - Do something with the embedding

```
import google.generativeai as genai
import os

genai.configure(api_key=os.environ["GEMINI_API_KEY"])

result = genai.embed_content(
        model="models/text-embedding-004",
        content="What is the meaning of life?")

print(str(result['embedding']))
```

Practical Applications of Embeddings

- **Semantic Search**:
  - Generate embeddings for documents and queries.
  - Find the most semantically similar documents.
- **Clustering**:
  - Use embeddings to cluster similar documents or texts together.
  - Visualize with 2D or 3D plots using PCA or t-SNE.
- **Recommendation Systems**:
  - Use embedding-based similarity for recommending items (e.g., products, articles).

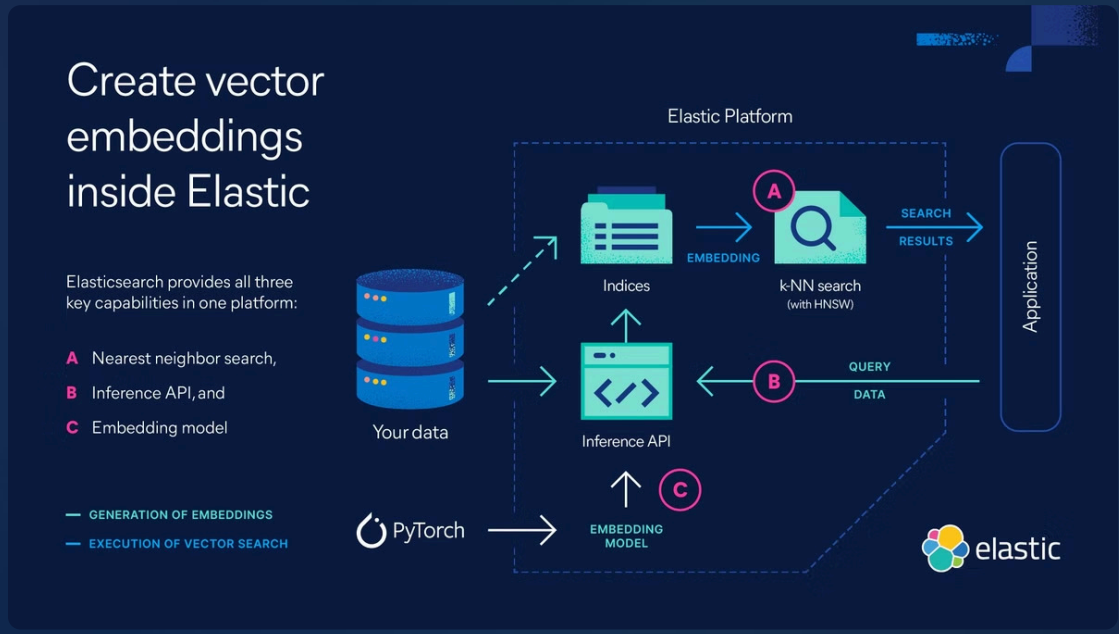
RAG Workflow



How do I store all these vectors?

If only… There was a database

- What is it?
- Why do we use it?
- What is the significance of it?



What are my options?

Vector DB	Pros	Cons
FAISS	High performance, flexible indexing, scalable, open-source.	Complex setup, memory management, limited API support, no metadata.
Pinecone	Fully managed, easy to use, scalable, real-time updates, advanced features.	Expensive, less control, no open-source option.
Weaviate	Hybrid search, ML model integration, graph + vector search, scalable.	Complex setup, higher resource consumption, fewer indexing options.
Milvus	High performance, multi-index support, scalable, open-source.	Complex deployment, resource consumption, limited real-time updates.
Chroma	Simple, user-friendly, optimized for embeddings, open-source.	Limited scalability, fewer advanced features, not ideal for large-scale.

Chroma, How does it work?

- Install Chroma
- Setup Chroma Client
- Create and add docs to collection
- Query

```
import chromadb

client = chromadb.Client()

collection = client.create_collection("all-my-documents")
collection.add(
    documents=["This is document1", "This is document2"], # we handle tokenization, embedding, and indexing automatically. You can skip that and add your own embeddings as well
    metadatas=[{"source": "notion"}, {"source": "google-docs"}], # filter on these!
    ids=["doc1", "doc2"], # unique for each doc
)

results = collection.query(
    query_texts=["This is a query document"],
    n_results=2,
    # where={"metadata_field": "is_equal_to_this"}, # optional filter
    # where_document={"$contains":"search_string"}  # optional filter
)
```

Key Takeaways

- **Embeddings**: Essential for advanced text analysis and search tasks.
- **Gemini Setup**: Remember to manage API keys and set usage limits for personal projects.
- **Practical Applications**: Semantic search, clustering, and recommendation systems are real-world uses of embeddings.
- **Next Steps**: Try building your own semantic search or clustering system using embeddings.