Batching upserts

VECTOR DATABASES FOR EMBEDDINGS WITH PINECONE

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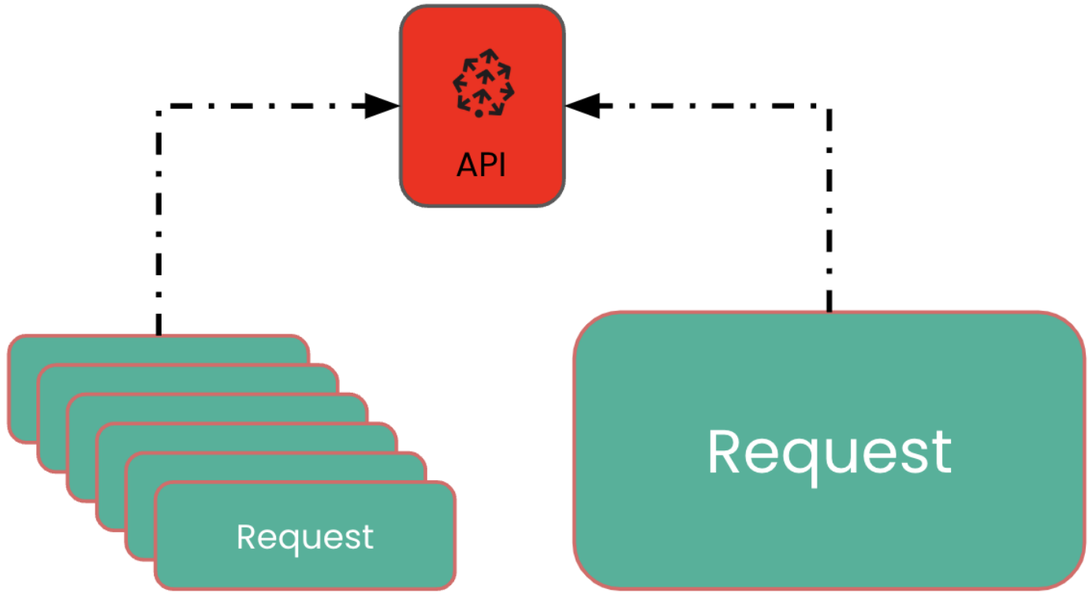
Upserting limitations

1. **Rate** of requests
2. **Size** of requests

- **Batching:** breaking requests up into smaller *chunks*



[1] https://docs.pinecone.io/reference/quotas-and-limits#rate-limits

Defining a chunking function

```
def chunks(iterable, batch_size=100):
    it = iter(iterable)
    chunk = tuple(itertools.islice(it, batch_size))
    while chunk:
        yield chunk
        chunk = tuple(itertools.islice(it, batch_size))
```

Sequential batching

- Splitting requests and sending them sequentially *one-by-one*

```
pc.Pinecone(api_key="YOUR API KEY")
index = pc.Index('datacamp-index')

for chunk in chunks(vectors):
    index.upsert(vectors=chunk)
```

Pros:

- Solve rate and size limiting

Cons:

- Really slow!

Parallel batching

- Splitting requests and sending them in *parallel*

```
pc = Pinecone(api_key="YOUR_API_KEY", pool_threads=30)

with pc.Index('datacamp-index', pool_threads=30) as index:
    async_results = [index.upsert(vectors=chunk, async_req=True)
        for chunk in chunks(vectors, batch_size=100)]

    [async_result.get() for async_result in async_results]
```

Let's practice!

VECTOR DATABASES FOR EMBEDDINGS WITH PINECONE

Multitenancy and namespaces

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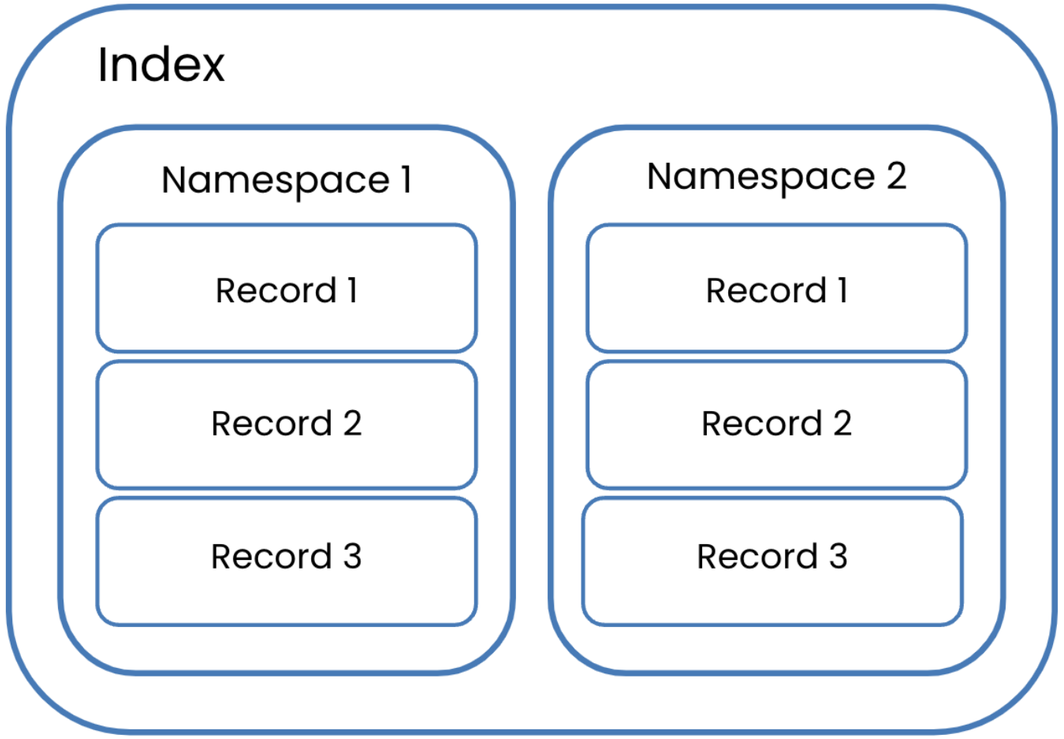
Multitenancy

- Serve multiple **tenants** in *isolation*
- Separate different customers' data
  - **Security** and **privacy**
- Reduce **query latency**



Multitenancy strategies

1. Namespaces
   - **Advantages:** Reduces the need for additional indexes
   - **Disadvantages:** Tenants share resources, complex data
2. Metadata Filtering
   - **Advantages:** Allows querying across multiple tenants
   - **Disadvantages:** Shared resources, challenging cost tracking
3. Separate Indexes
   - **Advantages:** Physically separates tenants, allocates individual resources
   - **Disadvantages:** Requires more effort and cost

Namespaces

- Created *implicitly* during upsertion if they don't exist

```
index.upsert(
  vectors=vector_set1, namespace="namespace1"
)
```

```
index.upsert(
  vectors=vector_set2, namespace="namespace2"
)
```

Inspecting namespaces

```
index.describe_index_stats()
```

```
{'dimension': 1536,
 'index_fullness': 0.0,
 'namespaces': {'namespace1': {'vector_count': 5},
                'namespace2': {'vector_count': 5}},
 'total_vector_count': 10}
```

Querying vectors from namespaces

```
query_result = index.query(
    vector=vector,
    namespace='namespace1',
    top_k=3
)
```

Deleting vectors from namespaces

```
index.delete(
    ids=["1", "2"],
    namespace='namespace1'
)
```

Let's practice!

VECTOR DATABASES FOR EMBEDDINGS WITH PINECONE

Semantic search with Pinecone

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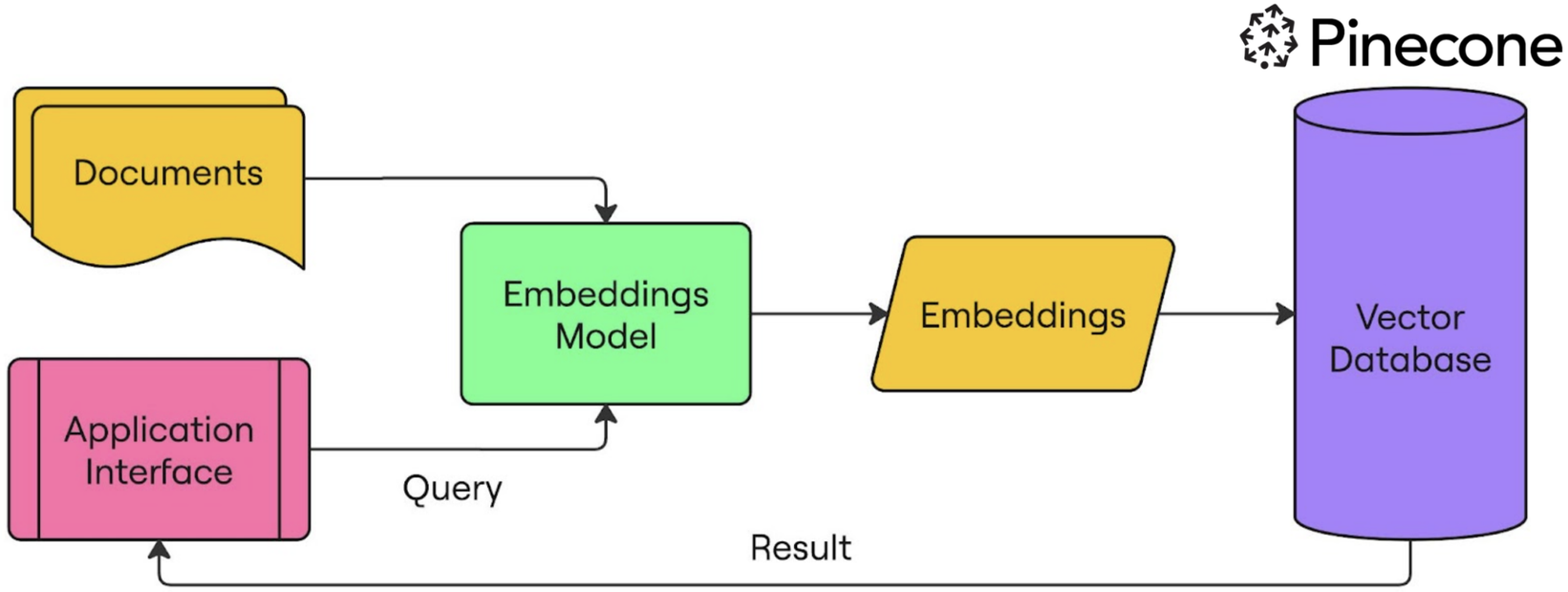
Semantic search engines

1. Embed and ingest documents into a Pinecone index
2. Embed a user query
3. Query the index with the embedded user query



Setting up Pinecone and OpenAI for semantic search

```
from openai import OpenAI
from pinecone import Pinecone, ServerlessSpec

client = OpenAI(api_key="OPENAI_API_KEY")
pc = Pinecone(api_key="PINECONE_API_KEY")

pc.create_index(
    name="semantic-search-datacamp",
    dimension=1536,
    spec=ServerlessSpec(cloud='aws', region='us-east-1')
)
index = pc.Index("semantic-search-datacamp")
```

Ingesting documents to Pinecone index

```
import pandas as pd
import numpy as np
from uuid import uuid4

df = pd.read_csv('squad_dataset.csv')
```

id	text	title
1	Architecturally, the school has a Catholic cha...	University of ...
2	The College of Engineering was established in....	University of ...
3	Following the disbandment of Destiny's Child in..	Beyonce
4	Architecturally, the school has a Catholic cha...	University of ...

Ingesting documents to Pinecone index

```
batch_limit = 100

for batch in np.array_split(df, len(df) / batch_limit):
    metadatas = [{"text_id": row['id'], "text": row['text'], "title": row['title']}
                 for _, row in batch.iterrows()]
    texts = batch['text'].tolist()
    ids = [str(uuid4()) for _ in range(len(texts))]

    response = client.embeddings.create(input=texts, model="text-embedding-3-small")
    embeds = [np.array(x.embedding) for x in response.data]

    index.upsert(vectors=zip(ids, embeds, metadatas), namespace="squad_dataset")
```

Ingesting documents to Pinecone index

```
index.describe_index_stats()
```

```
{'dimension': 1536, 'index_fullness': 0.02,
 'namespaces': {'squad_dataset': {'vector_count': 2000}},
 'total_vector_count': 2000}
```

Querying with Pinecone

```
query = "To whom did the Virgin Mary allegedly appear in 1858 in Lourdes France?"

query_response = client.embeddings.create(
    input=query,
    model="text-embedding-3-small")
query_emb = query_response.data[0].embedding

retrieved_docs = index.query(vector=query_emb,
                             top_k=3,
                             namespace=namespace,
                             include_metadata=True)
```

Querying with Pinecone

```
for result in retrieved_docs['matches']:
    print(f"{round(result['score'], 2)}: {result['metadata']['text']}")
```

```
0.41: Architecturally, the school has a Catholic character. Atop the Main Building
gold dome is a golden statue of the Virgin Mary...

0.3: Because of its Catholic identity, a number of religious buildings stand on
campus. The Old College building has become one of two seminaries...

0.29: Within the white inescutcheon, the five quinas (small blue shields) with
their five white bezants representing the five wounds...
```

Time to build!

VECTOR DATABASES FOR EMBEDDINGS WITH PINECONE

RAG chatbot with Pinecone and OpenAI

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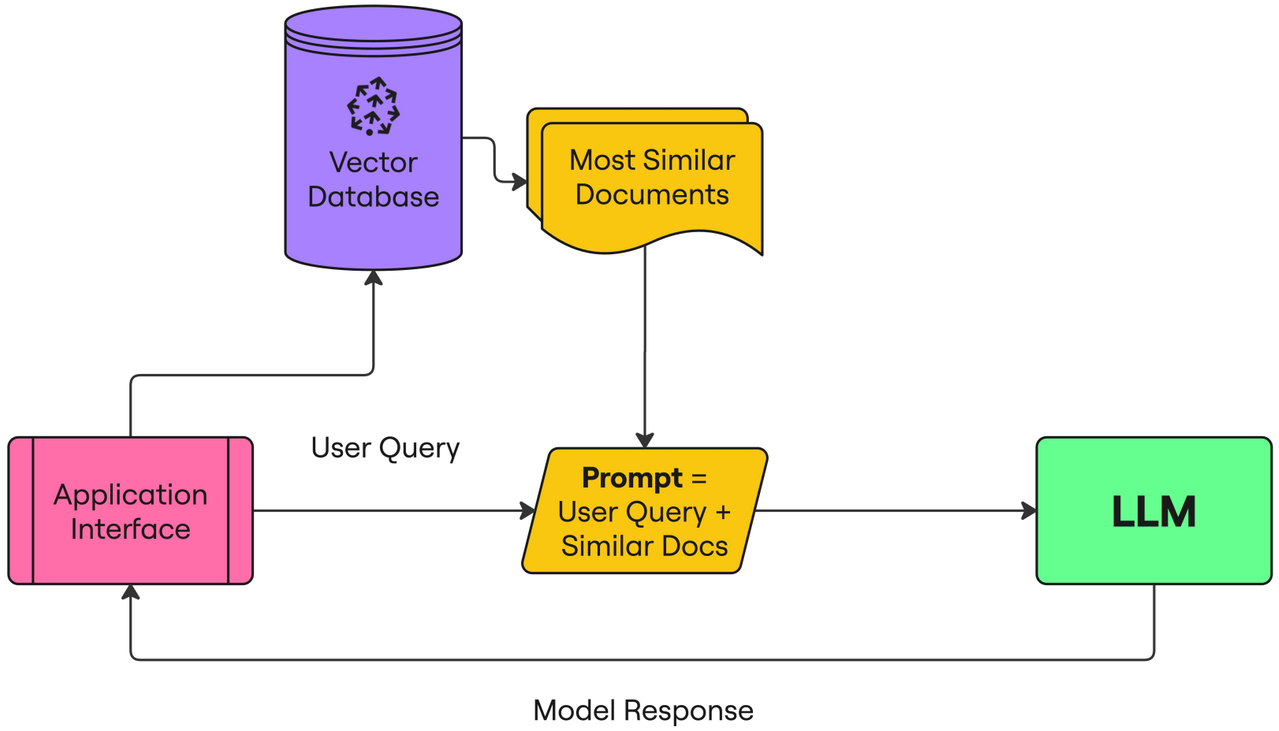
Retrieval Augmented Generation (RAG)

1. Embed user query
2. Retrieve similar documents
3. Added documents to **prompt**



Initialize Pinecone and OpenAI

```
from openai import OpenAI
from pinecone import Pinecone
import pandas as pd
from uuid import uuid4

client = OpenAI(api_key="OPENAI_API_KEY")
pc = Pinecone(api_key="PINECONE_API_KEY")

index = pc.Index("semantic-search-datacamp")
```

YouTube transcripts

```
youtube_df = pd.read_csv('youtube_rag_data.csv')
```

```
| id | blob | channel_id | end | published | start | text | title | url |
|----|------|------------|-----|-----------|-------|------|-------|-----|
|int | dict | str        | int | datetime  | int   | str  | str   | str |
```

Ingesting documents

```
batch_limit = 100

for batch in np.array_split(youtube_df, len(youtube_df) / batch_limit):
    metadatas = [{"text_id": row['id'], "text": row['text'],
      "title": row['title'], "url": row['url'],
      "published": row['published']} for  _, row in batch.iterrows()]
    texts = batch['text'].tolist()
    ids = [str(uuid4()) for _ in range(len(texts))]

    response = client.embeddings.create(input=texts, model="text-embedding-3-small")
    embeds = [np.array(x.embedding) for x in response.data]

    index.upsert(vectors=zip(ids, embeds, metadatas), namespace='youtube_rag_dataset')
```

Retrieval function

```
def retrieve(query, top_k, namespace, emb_model):
    query_response = client.embeddings.create(input=query, model=emb_model)
    query_emb = query_response.data[0].embedding

    retrieved_docs = []
    sources = []
    docs = index.query(vector=query_emb, top_k=top_k,
                       namespace='youtube_rag_dataset', include_metadata=True)

    for doc in docs['matches']:
        retrieved_docs.append(doc['metadata']['text'])
        sources.append((doc['metadata']['title'], doc['metadata']['url']))
    return retrieved_docs, sources
```

Retrieval output

```
query = "How to build next-level Q&A with OpenAI"
documents, sources = retrieve(query, top_k=3, namespace='youtube_rag_dataset',
                              emb_model="text-embedding-3-small")
```

```
Document: To use for Open Domain Question Answering. We're going to start...
Source: How to build a Q&A AI in Python [...], https://youtu.be/w1dMEWm7jBc

Document: Over here we have Google and we can ask Google questions...
Source: How to build next-level Q&A with OpenAI, https://youtu.be/coaaSxys5so

Document: We need vector database to enhance the quality of Q&A systems...
Source: How to Build Custom Q&A Transfo [...], https://youtu.be/ZIRmXKHp0-c
```

Prompt with context builder function

```
def prompt_with_context_builder(query, docs):
    delim = '\n\n---\n\n'
    prompt_start = 'Answer the question based on the context below.\n\nContext:\n'
    prompt_end = f'\n\nQuestion: {query}\nAnswer:'

    prompt = prompt_start + delim.join(docs) + prompt_end
    return prompt
```

Prompt with context builder output

```
query = "How to build next-level Q&A with OpenAI"
context_prompt = prompt_with_context_builder(query, documents)
```

```
Answer the question based on the context below.

Context:
to use for Open Domain Question Answering. We're going to start with a few examples. Over here we have Google and w
e can ask Google questions like we would a normal person. So we can say, how do I tie my shoelaces? So what we have
right here is three components to the question and answer. And I want you to remember these because these are relev
ant for what we are going to be building. We have the query at the top. We have what we can refer to as a context,
which is the video, which is where we're getting this small, more specific answer from. And we can ask another ques
tion. Is Google SkyNet? So we have our question at the top. We have this paragraph, which is our context. And then
we have the answer, which is yes, which is highlighted here. So it's slightly different to the previous one where w
e had the video. This time we have actual text, which is our context. And this is more aligned with what we will se
e throughout this video as well. Now, what we really want to be asking here is one, how does Google do that?

Question: How to build next-level Q&A with OpenAI
Answer:
```

Question-answering function

```
def question_answering(prompt, sources, chat_model):
    sys_prompt = "You are a helpful assistant that always answers questions."
    res = client.chat.completions.create(
        model=chat_model,
        messages=[{"role": "system", "content": sys_prompt},
            {"role": "user", "content": prompt}
        ], temperature=0)
    answer = res.choices[0].message.content.strip()
    answer += "\n\nSources:"
    for source in sources:
        answer += "\n" + source[0] + ": " + source[1]
    return answer
```

Question-answering output

```
query = "How to build next-level Q&A with OpenAI"
answer = question_answering(prompt_with_context, sources,
                            chat_model='gpt-4o-mini')
```

```
To build next-level Q&A with OpenAI, you can start by fine-tuning a Q&A Transformer model using relevant datasets s
uch as the SQuAD dataset (Stanford Question Answering Dataset). This involves downloading the dataset, organizing i
t in a folder, and then using it to train your model. Additionally, you can utilize OpenAI's generative models like
GPT-2 to enhance the question-answering capabilities by providing context and prompting the model to generate intel
ligent responses. By following these steps and leveraging transformer-based solutions, you can create a more advanc
ed Q&A system with OpenAI technology.

Sources:
How to build a Q&A AI in Python (Open-domain Question-Answering): https://youtu.be/w1dMEWm7jBc
How to build next-level Q&A with OpenAI: https://youtu.be/coaaSxys5so
How to Build Custom Q&A Transformer Models in Python: https://youtu.be/ZIRmXkHp0-c
```

Putting it all together

```
query = "How to build next-level Q&A with OpenAI"
documents, sources = retrieve(query, top_k=3,
                              namespace='youtube_rag_dataset',
                              emb_model="text-embedding-3-small")
prompt_with_context = prompt_with_context_builder(query, documents)
answer = question_answering(prompt_with_context, sources,
                            chat_model='gpt-4o-mini')
```

Let's practice!

VECTOR DATABASES FOR EMBEDDINGS WITH PINECONE

Congratulations!

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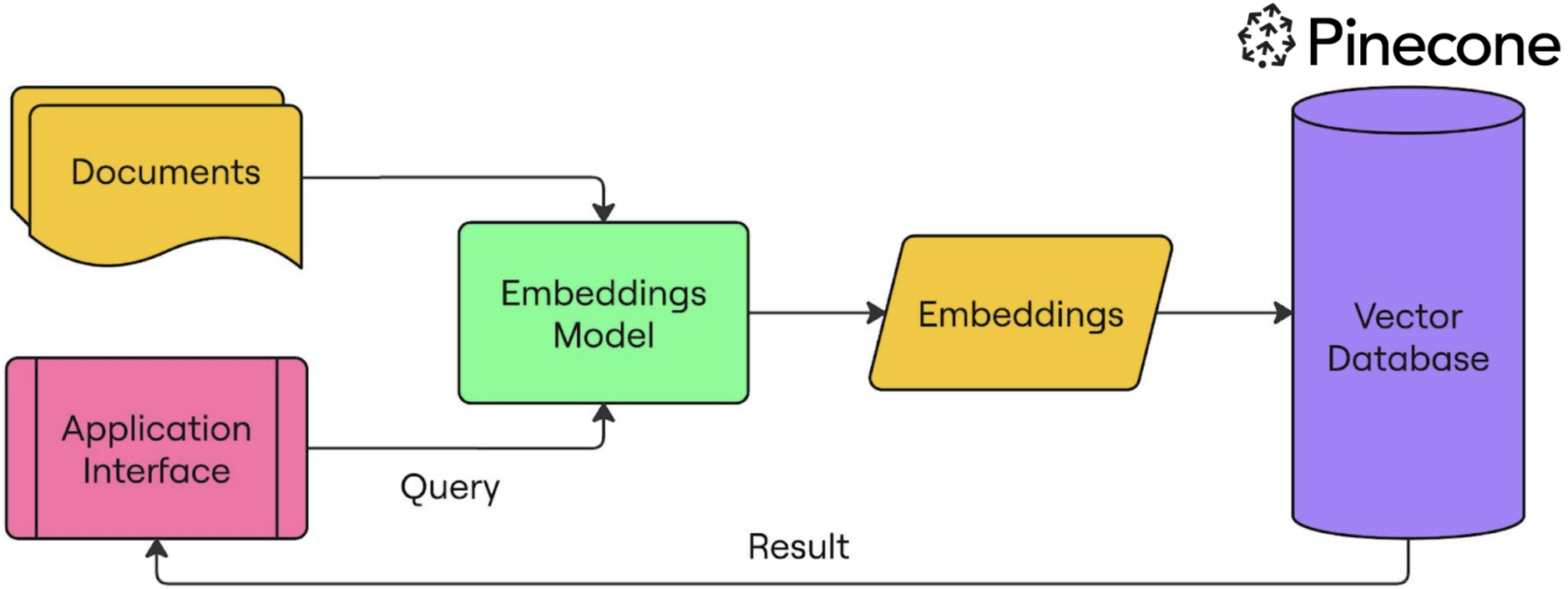
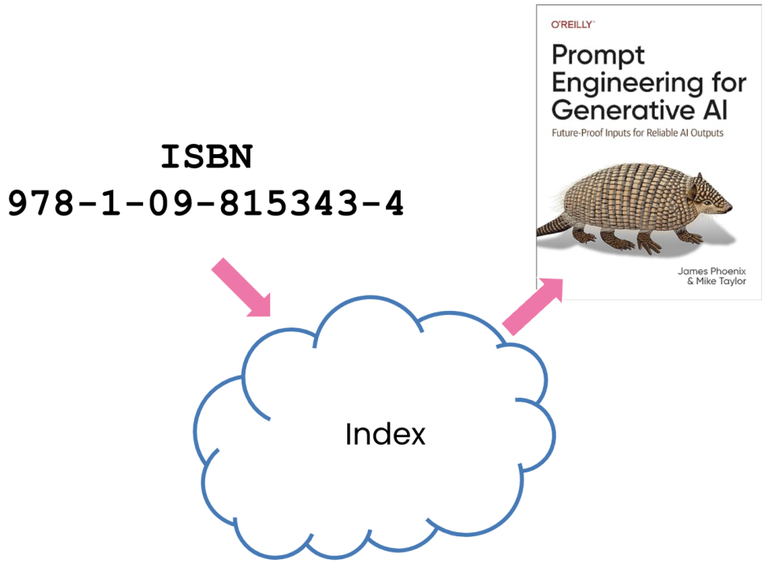
Chapter 1 - Introduction to Pinecone

- Created an index → `pc.create_index()`
- Connect to it → `pc.Index()`
- Ingested vectors → `index.upsert()`



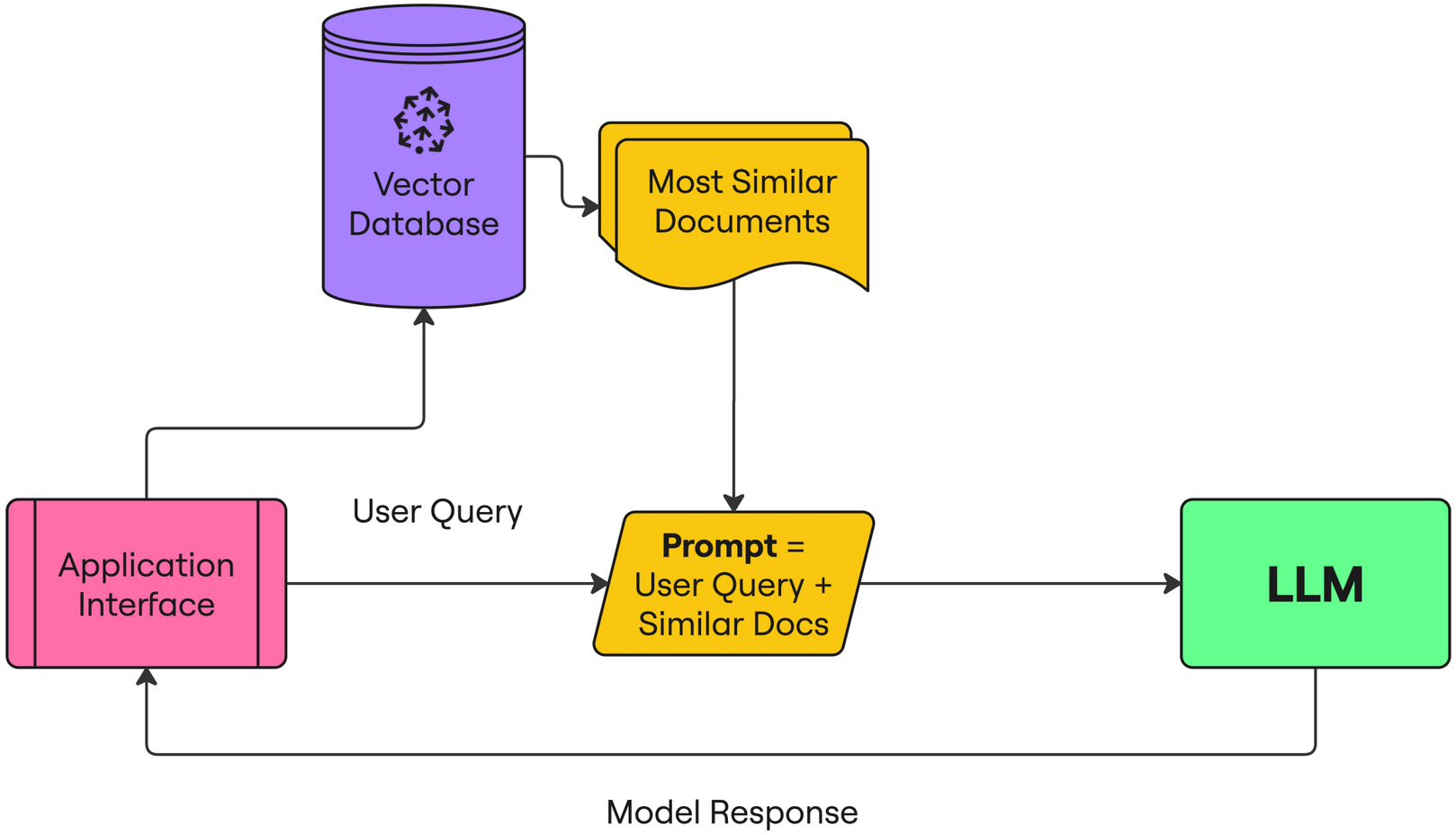
Chapter 2 - Pinecone Vector Manipulation in Python

Fetching



Querying

Chapter 3 - Performance Tuning and AI Applications



What's next?

Integrations

- Setting up your Knowledge Base for Amazon Bedrock
- Retrieval Augmentation in LangChain
- Hugging Face Inference Endpoints

Pinecone

Amazon SageMaker

Amazon Bedrock

Congratulations!

VECTOR DATABASES FOR EMBEDDINGS WITH PINECONE