Vector databases for embedding systems

INTRODUCTION TO EMBEDDINGS WITH THE OPENAI API

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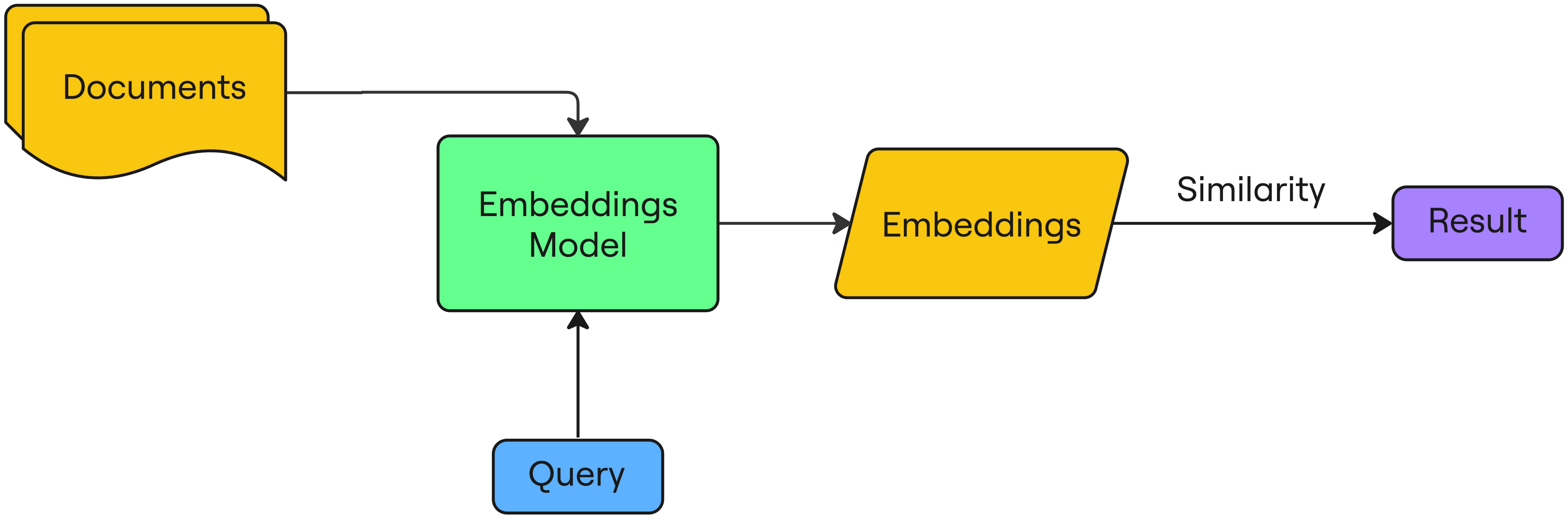
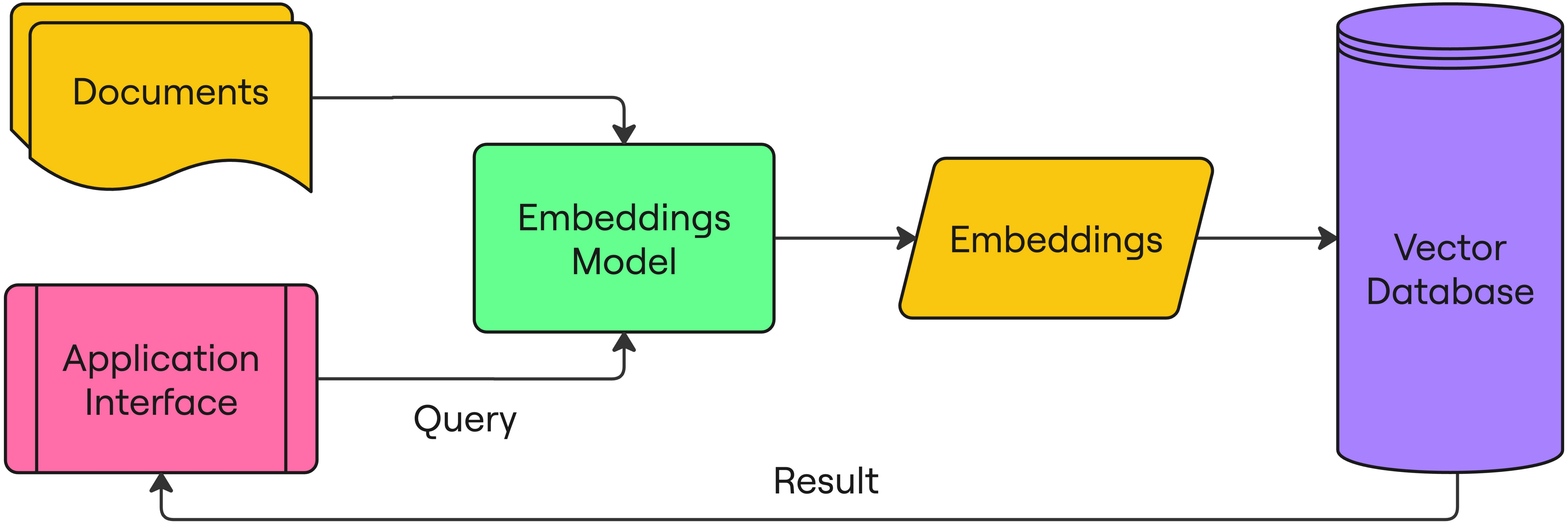
Limitations of the current approach

- Loading all the embeddings into memory (1536 floats ~ **13kB/embedding**)
- Recalculated embeddings for each new query
- Calculating cosine distances for every embedding and sorting is slow and **scales linearly**



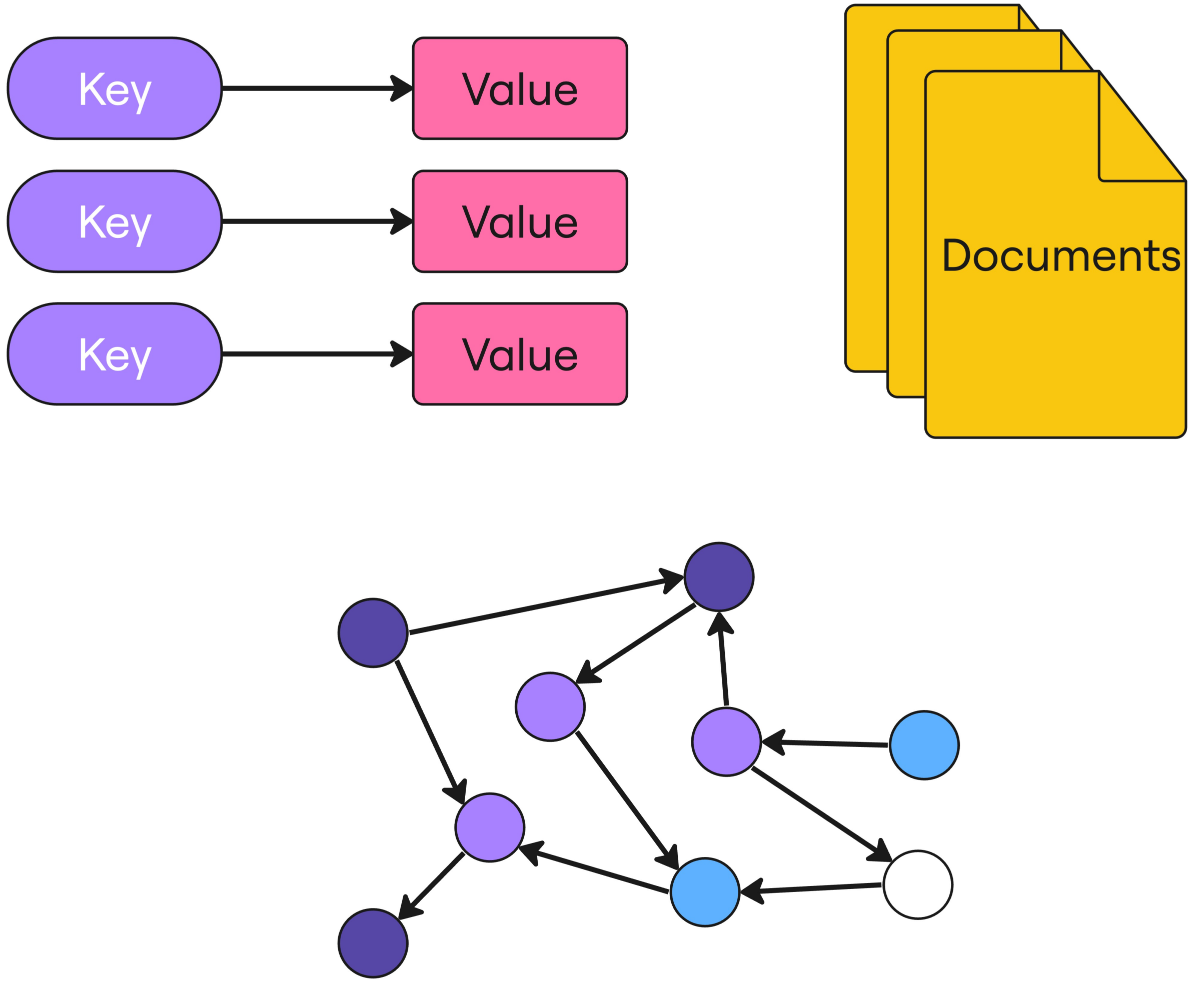
Vector databases

- Embedded documents are *stored* and *queried* from the **vector database**



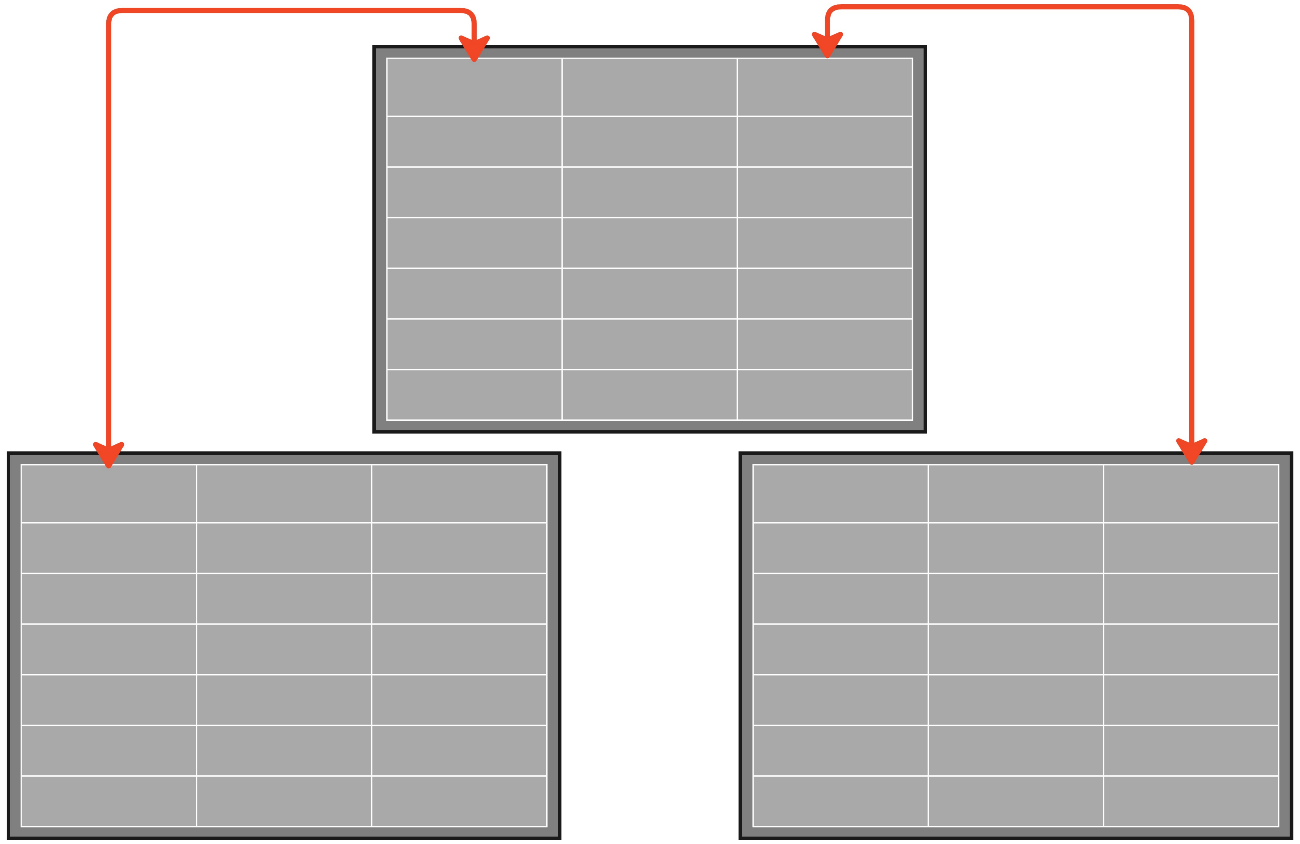
NoSQL Database

- More flexible structure that allows for *faster querying*



SQL/Relational Database

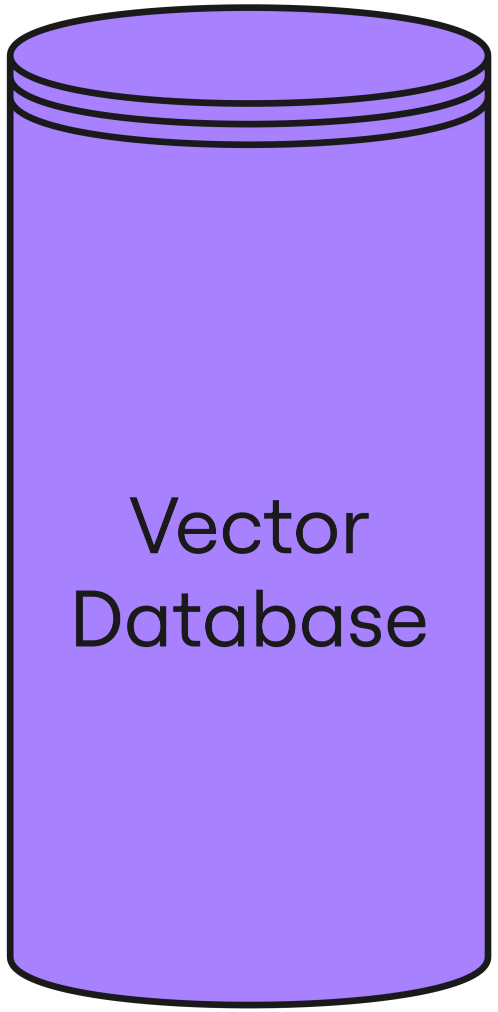
- Structured data into tables, rows, and columns



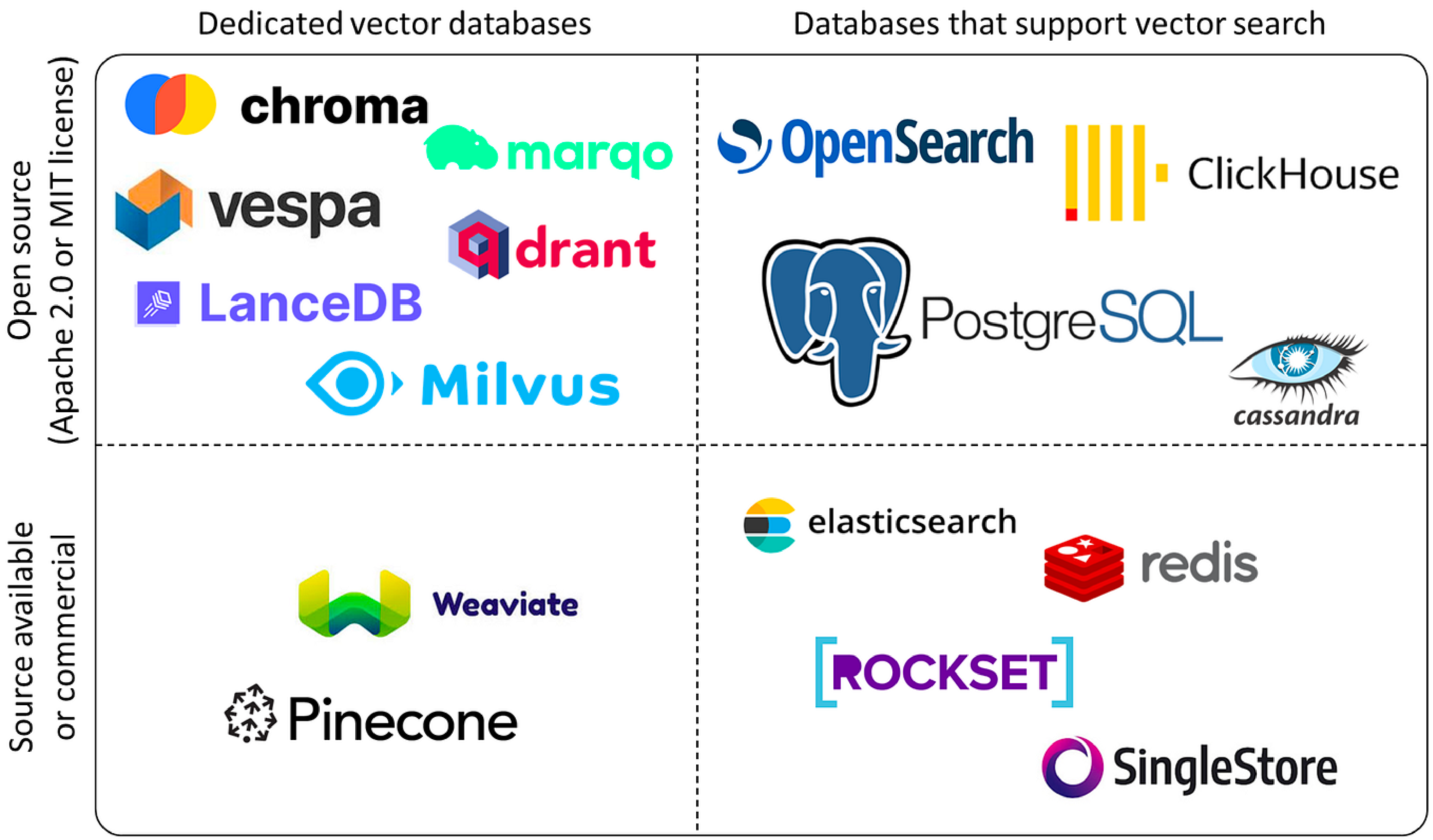
Components to store

- Embeddings
- Source texts
- Metadata
  - IDs and references
  - Additional data useful for filtering results

Top tip: Don't store the source text as metadata!



The vector database landscape



[1] Image Credit: Yingjun Wu

Which solution is best?

- **Database management:**
  - Managed → more expensive but lowers workload
  - Self-managed → cheaper but requires time and expertise
- **Open source or commercial?**
  - Open source → flexible and cost-effective
  - Commercial → better support, more advanced features, and compliance
- **Data models:** does the type of data lend itself to a particular database type?
- **Specific features:** does your use case depend on specific functionality, such as multi-modal storage?

chroma

Let's practice!

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Creating vector databases with ChromaDB

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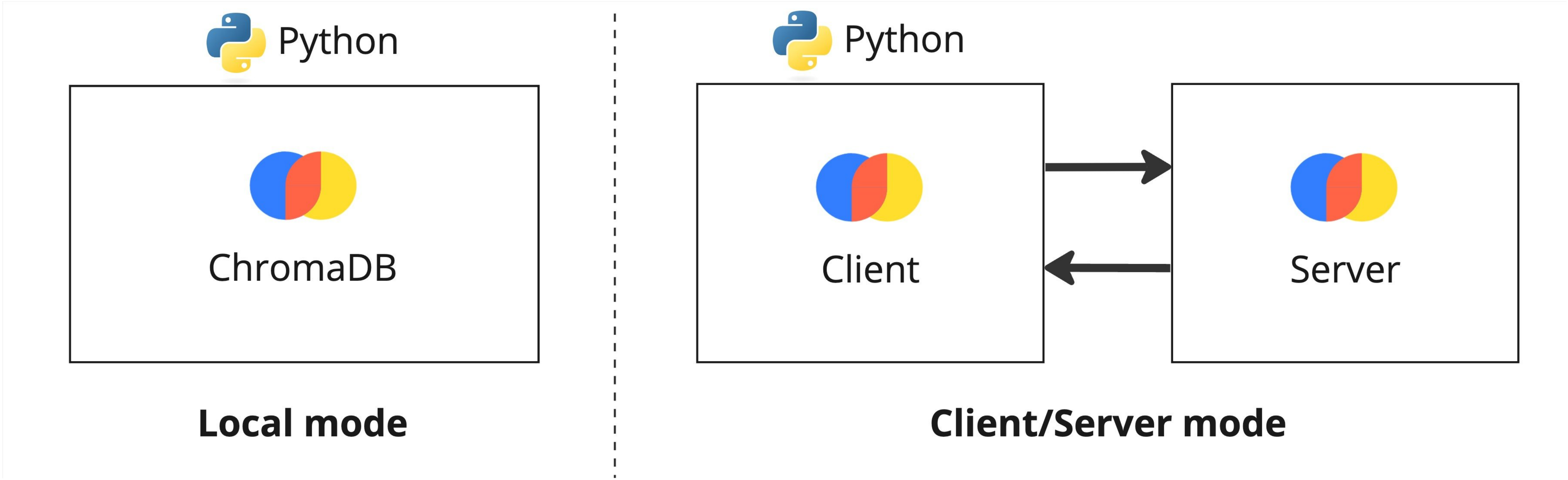
datacamp

Installing ChromaDB

- *ChromaDB* is a simple yet powerful vector database
- Two flavors:
  - **Local:** great for development and prototyping
  - **Client/Server:** made for production



Connecting to the database

```
import chromadb

client = chromadb.PersistentClient(path="/path/to/save/to")
```

- Data will be persisted to disk

Creating a collection

- Collections are analogous to tables

```
from chromadb.utils.embedding_functions import OpenAIEmbeddingFunction
```

```
collection = client.create_collection(
    name="my_collection",
    embedding_function=OpenAIEmbeddingFunction(
        model_name="text-embedding-3-small",
        api_key="..."
    )
)
```

- Collections are able to create embeddings automatically

Inspecting collections

```
client.list_collections()
```

```
[Collection(name=my_collection)]
```

Inserting embeddings

Single document

```
collection.add(ids=["my-doc"], documents=["This is the source text"])
```

- IDs must be provided
- Embeddings will be created by the collection!

Multiple documents

```
collection.add(
  ids=["my-doc-1", "my-doc-2"],
  documents=["This is document 1", "This is document 2"]
)
```

Inspecting a collection

Counting documents in a collection

```
collection.count()
```

```
3
```

Inspecting a collection

Peeking at the first 10 items

```
collection.peek()
```

```
{'ids': ['my-doc', 'my-doc-1', 'my-doc-2'],
 'embeddings': [[...], [...], [...]],
 'documents': ['This is the source text',
  'This is document 1',
  'This is document 2'],
 'metadatas': [None, None, None]}
```

Retrieving items

```python
collection.get(ids=["s59"])
```

```
{'ids': ['s59'],
 'embeddings': None,
 'metadatas': [None],
 'documents': ['Title: Naruto Shippûden the Movie: The Will of Fire (Movie)\nDescription: When ...'],
 'uris': None,
 'data': None}
```

Netflix dataset

```
Title: Kota Factory (TV Show)
Description: In a city of coaching centers known to train India's finest...
Categories: International TV Shows, Romantic TV Shows, TV Comedies
```

```
Title: The Last Letter From Your Lover (Movie)
Description: After finding a trove of love letters from 1965, a reporter sets...
Categories: Dramas, Romantic Movies
```

Estimating embedding cost

- Embedding model (`text-embedding-3-small`) costs $0.00002/1k tokens

```
cost = 0.00002 * len(tokens)/1000
```

- Count tokens with the `tiktoken` library
  - `pip install tiktoken`

[1] https://openai.com/pricing

Estimating embedding cost

```
import tiktoken

enc = tiktoken.encoding_for_model("text-embedding-3-small")

total_tokens = sum(len(enc.encode(text)) for text in documents)

cost_per_1k_tokens = 0.00002

print('Total tokens:', total_tokens)
print('Cost:', cost_per_1k_tokens * total_tokens/1000)
```

```
Total tokens: 444463
Cost: 0.00888926
```

Let's practice!

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Querying and updating the database

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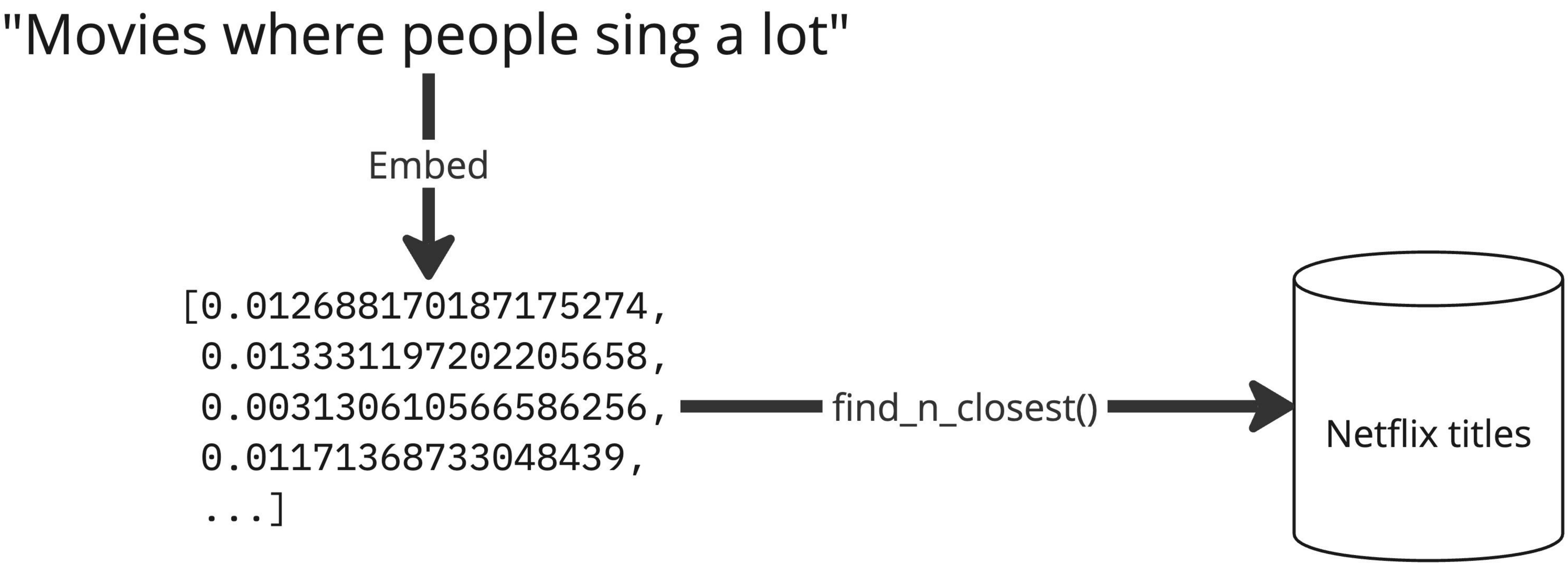
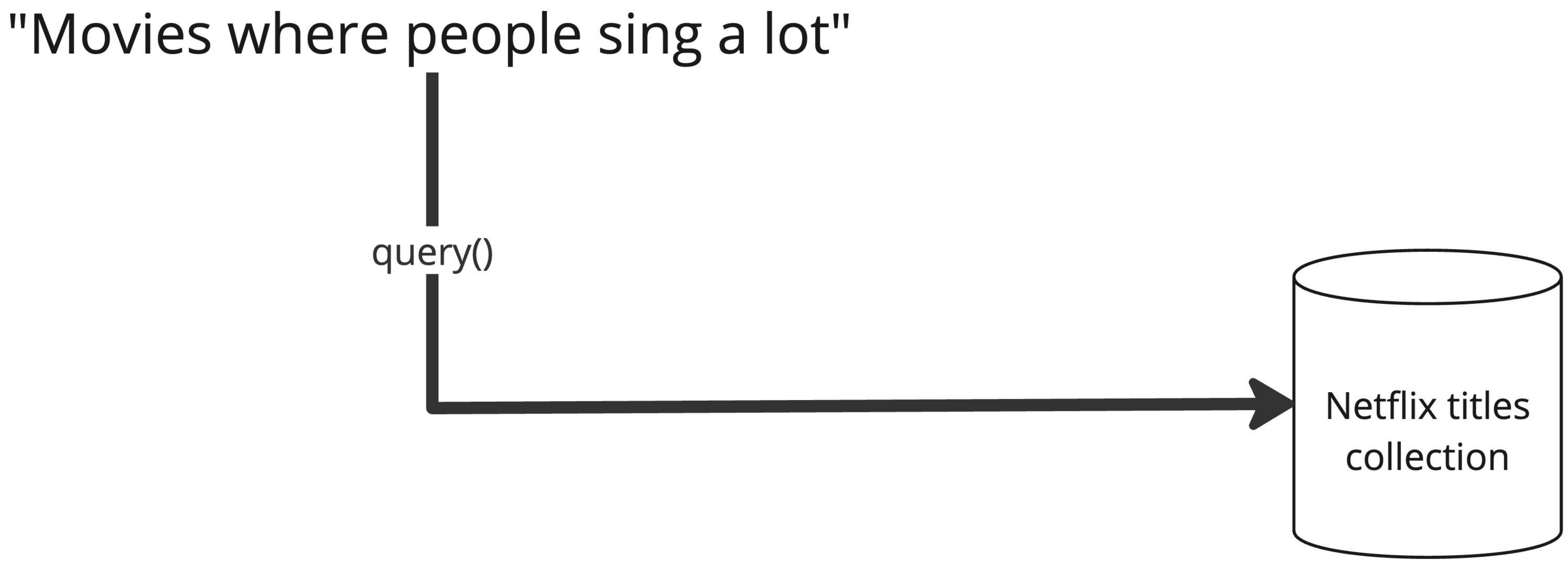
Querying the database



Querying the database



Retrieve the collection

```
from chromadb.utils.embedding_functions import OpenAIEmbeddingFunction

collection = client.get_collection(
    name="netflix_titles",
    embedding_function=OpenAIEmbeddingFunction(api_key="...")
)
```

- Must be specify *the same embedding function* used when adding data to the collection

Querying the collection

```python
result = collection.query(
  query_texts=["movies where people sing a lot"],
  n_results=3
)
print(result)
```

```
{'ids': [['s4068', 's293', 's2213']],
 'embeddings': None,
 'documents': [['Title: Quién te cantará (Movie)\nDescription: When a near-...',
   'Title: Quartet (Movie)\nDescription: To save their posh retirement home, ...',
   'Title: Sing On! Spain (TV Show)\nDescription: In this fast-paced, high-...']],
 'metadatas': [[None, None, None]],
 'distances': [[0.350419282913208, 0.36049118638038635, 0.37080681324005127]]
```

`query()` returns a dict with multiple keys:

- `ids` : The ids of the returned items
- `embeddings` : The embeddings of the returned items
- `documents` : The source texts of the returned items
- `metadatas` : The metadatas of the returned items
- `distances` : The distances of the returned items from the query text

```
{'ids': [...],
 'embeddings': None,
 'documents': [...],
 'metadatas': [...],
 'distances': [...]}
```

```
'ids': [['s4068', 's293', 's2213']]
```

```
result = collection.query(
  query_texts=["movies where people sing a lot"],
  n_results=3
)
```

- First list corresponds to the first query_text
- Multiple query texts will return multiple lists

```
{'ids': [['s4068', 's293', 's2213']],

 'embeddings': None,

 'documents': [["Title: Quién te cantará (Movie)\nDescription: When a near-drowning leaves a
famous singer from the '90s with amnesia, she hires a karaoke singer who can imitate her to
prep her for a comeback tour.\nCategories: Dramas, Independent Movies, International Movies",

   'Title: Quartet (Movie)\nDescription: To save their posh retirement home, former opera
stars plan a gala recital – until the biggest diva among them refuses to sing.\nCategories:
Comedies, Dramas, Independent Movies',

   'Title: Sing On! Spain (TV Show)\nDescription: In this fast-paced, high-energy karaoke
competition, singers from all walks of life battle it out for up to 30,000 euros!\nCategories:
International TV Shows, Reality TV, Spanish-Language TV Shows']],

 'metadatas': [[None, None, None]],

 'distances': [[0.350419282913208, 0.36049118638038635, 0.37080681324005127]]}
```

Updating a collection

```
collection.update(
  ids=["id-1", "id-2"],
  documents=["New document 1", "New document 2"]
)
```

- Include *only* the fields to update, other fields will be unchanged
- Collection will automatically create embeddings

Upserting a collection

```
collection.upsert(
  ids=["id-1", "id-2"],
  documents=["New document 1", "New document 2"]
)
```

- If IDs are missing → add them
- If IDs are present → update them

Deleting

Delete items from a collection

```
collection.delete(ids=["id-1", "id-2"])
```

Delete all collections and items

```
client.reset()
```

- **Warning:** this will delete **everything** in the database!

Let's practice!

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Multiple queries and filtering

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Movie recommendations based on multiple datapoints

- Terrifier (id: `'s8170'`)
- Strawberry Shortcake: Berry Bitty Adventures (id: `'s8103'`)

Multiple query texts

```
reference_ids = ['s8170', 's8103']

reference_texts = collection.get(ids=reference_ids)["documents"]

result = collection.query(
  query_texts=reference_texts,
  n_results=3
)
```

Multiple query texts result

```
{'ids': [['s8170', 's6939', 's7000'],['s8103', 's2968', 's3085']],
 'embeddings': None,
 'documents': [['Title: Terrifier (Movie)...',
   'Title: Haunters: The Art of the Scare (Movie)...',
   'Title: Horror Story (Movie)...'],
  ["Title: Strawberry Shortcake: Berry Bitty Adventures (TV Show)...",
   "Title: Shopkins (TV Show)...",
   "Title: Rainbow Ruby (TV Show)..."]],
 'metadatas': [[None, None, None], [None, None, None]],
 'distances': [[0.00, 0.25, 0.26], [0.00, 0.25, 0.28]]}
```

Adding metadata

```python
import csv

ids = []
metadatas = []

with open('netflix_titles.csv') as csvfile:
  reader = csv.DictReader(csvfile)
  for i, row in enumerate(reader):
    ids.append(row['show_id'])
    metadatas.append({
      "type":row['type'],
      "release_year": int(row['release_year']
    })
```

- Create a list of dicts for the metadatas
- Create a list of IDs to add them to the existing items

Adding and querying metadatas

```
collection.update(ids=ids, metadatas=metadatas)
```

```
result = collection.query(
    query_texts=reference_texts,
    n_results=3,
    where={
        "type": "Movie"
    }
)
```

Where operators

```
where={
  "type": "Movie"
}
```

is the same as

```
where={
  "type": {
    "$eq": "Movie"
  }
}
```

List of operators:

- `$eq` - equal to (string, int, float)
- `$ne` - not equal to (string, int, float)
- `$gt` - greater than (int, float)
- `$gte` - greater than or equal to (int, float)
- `$lt` - less than (int, float)
- `$lte` - less than or equal to (int, float)

Multiple where filters

```
where={
    "$and": [
        {"type":
            {"$eq": "Movie"}
        },
        {"release_year":
             {"$gt": 2020}
        }
    ]
}
```

- `$or` : filter based on *at least* one condition

```
Title: A Classic Horror Story (Movie) [...]
===
Title: Nightbooks (Movie) [...]
===
Title: Irul (Movie) [...]
===
Title: Intrusion (Movie) [...]
===
Title: Things Heard & Seen (Movie) [...]
===
Title: A StoryBots Space Adventure (Movie) [...]
```

Let's practice!

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Congratulations!

INTRODUCTION TO EMBEDDINGS WITH THE OPENAI API

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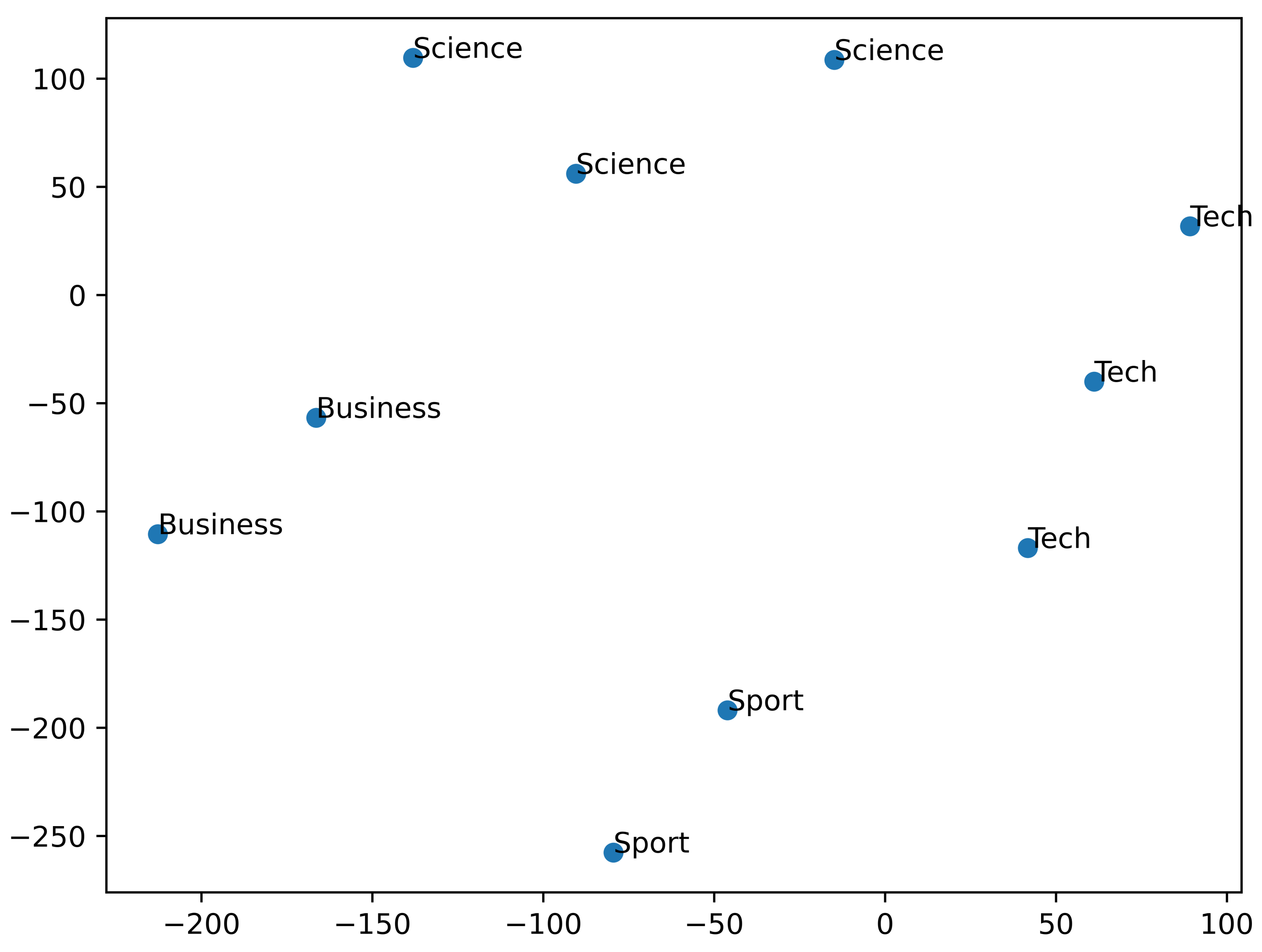
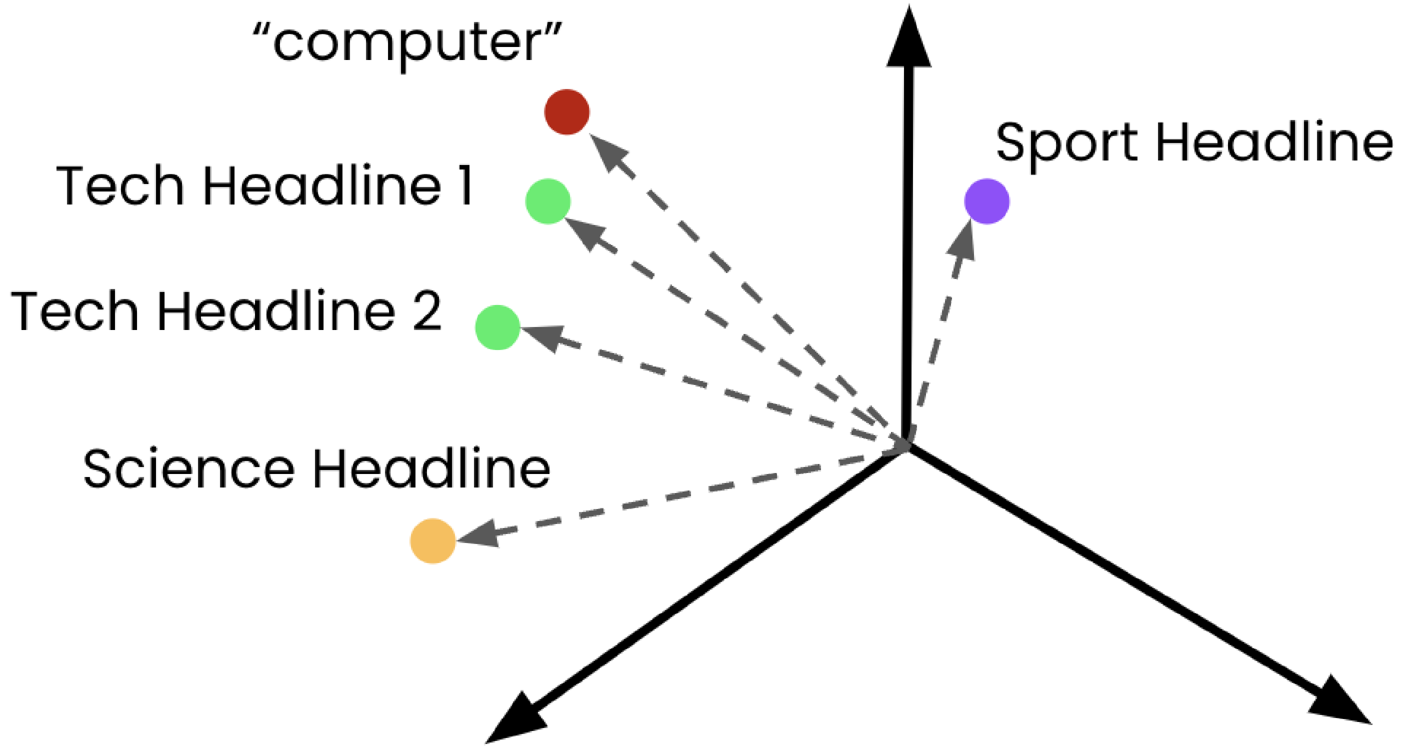
Chapter 1 - What are Embeddings?

- **Embeddings:** *vector*/numerical representation of text
- Capture the *semantic meaning* of text
- Used OpenAI's Embedding model
- Can use the *cosine distance* to find similar texts
- Unlocks semantic search, recommendation engines, etc.

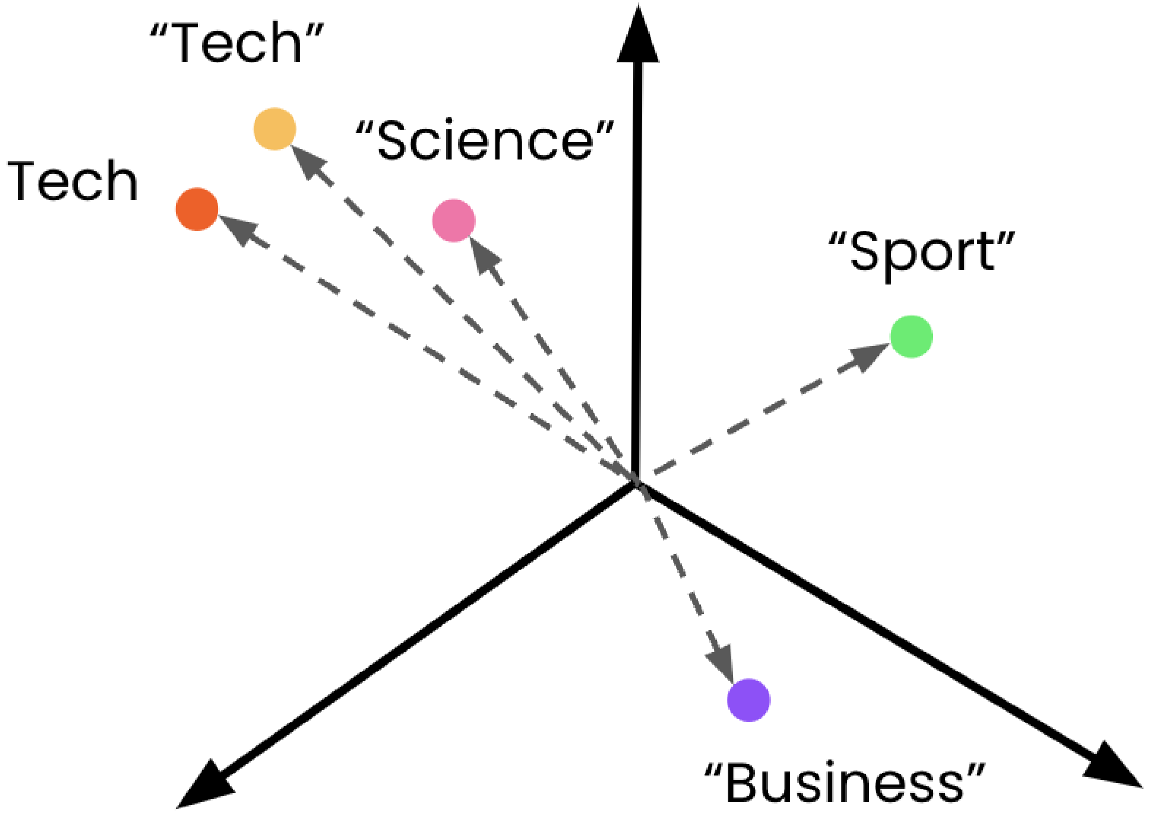


Chapter 2 - Embeddings for AI Applications

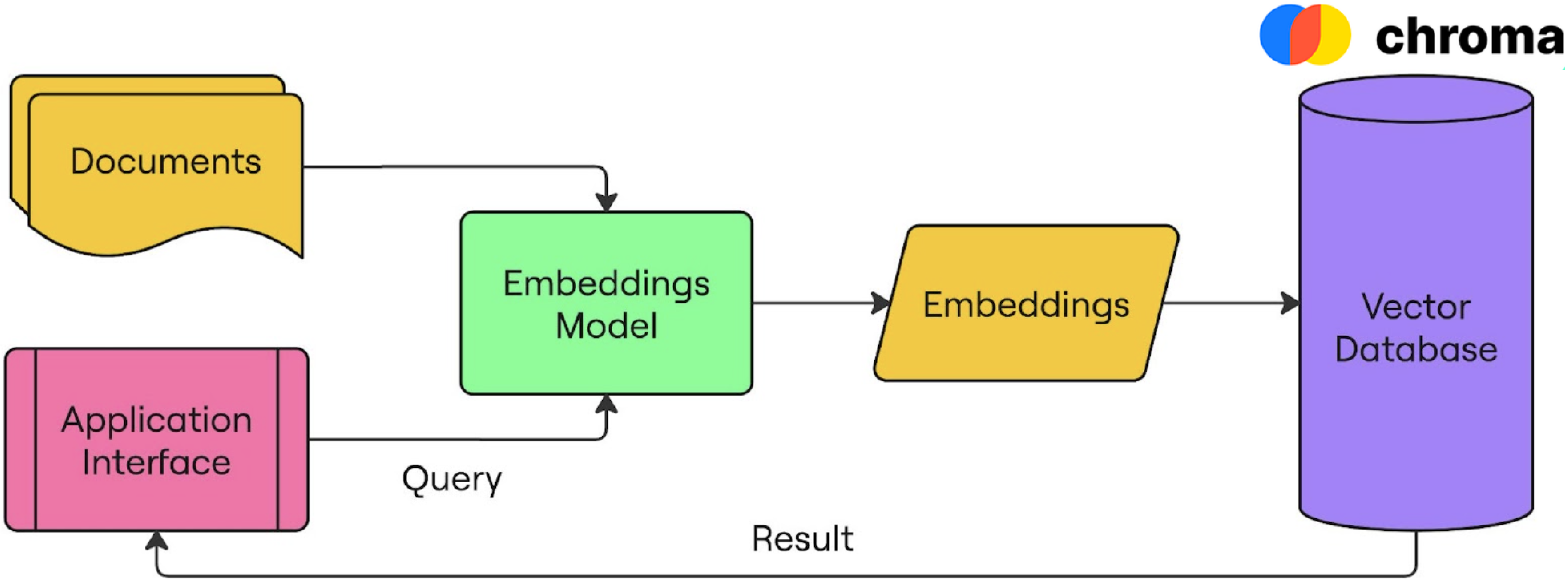
Semantic search and recommendation



Classification



Chapter 3 - Vector Databases



Where next?

Cloud-based, managed vector databases

- **Pinecone:**
  - Semantic Search with Pinecone (Code-along)
- **Weaviate:**
  - Vector Databases for Data Science with Weaviate in Python (Code-along)

Frameworks for creating applications

- **LangChain:**
  - How to Build LLM Applications with LangChain (Tutorial)
  - Introduction to Large Language Models with GPT & LangChain (Code-along)

Let's practice!

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