

WORKSHOP  
Generative AI



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Data and Artificial Intelligence  
Microsoft

# Multimodal Retrieval Augmented Generation

ODSC  
EAST 2024

BOSTON  
APRIL 23–25

THE LEADING  
AI TRAINING CONFERENCE



# Getting Started with MM RAG

An implementation with GPT-4v and  
Llama-Index



# Agenda

**Tip:** Download the workshop material to start familiarizing with code and slides.



**How:** Scan the QR code below!



1

Intro to RAG

2

Embeddings and VectorDB

3

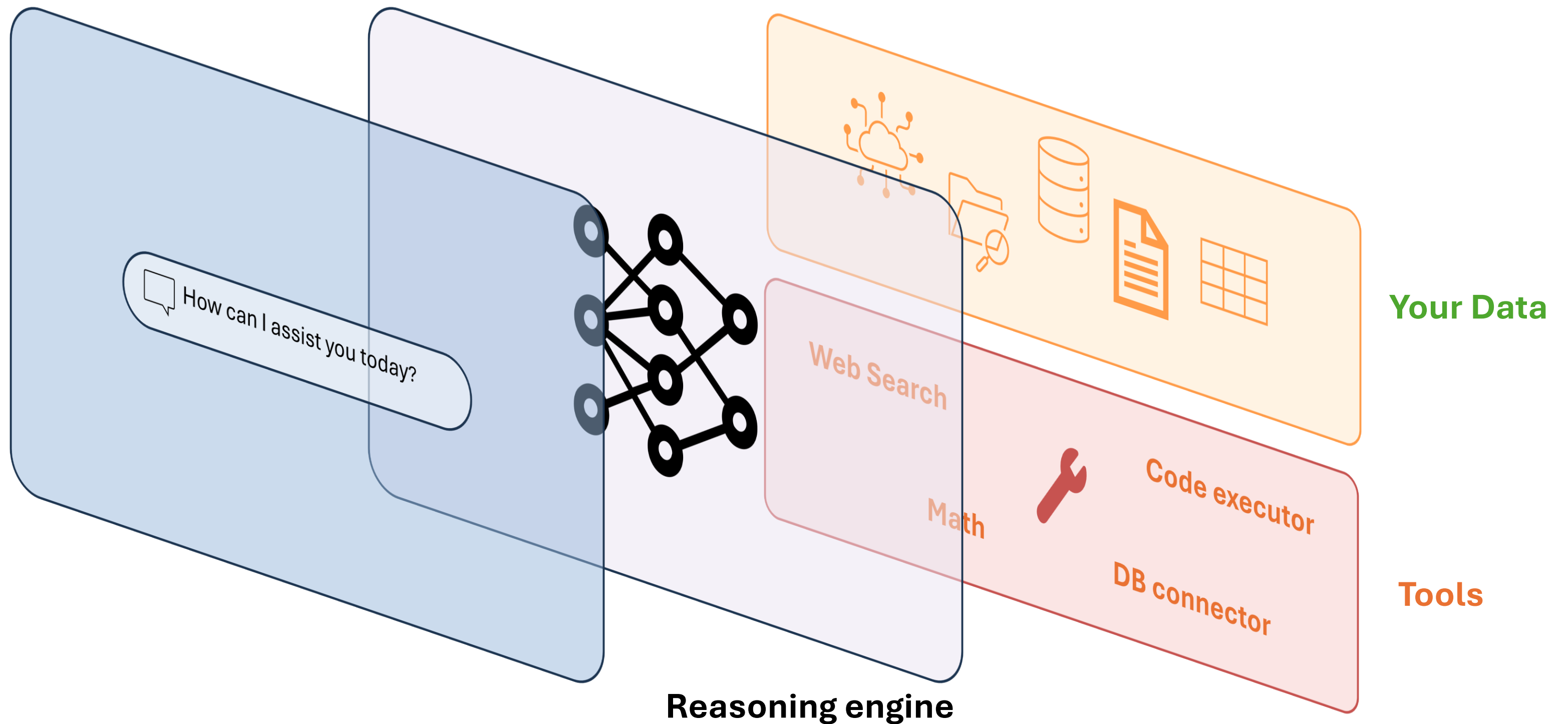
Multimodal RAG

4

Demo Time

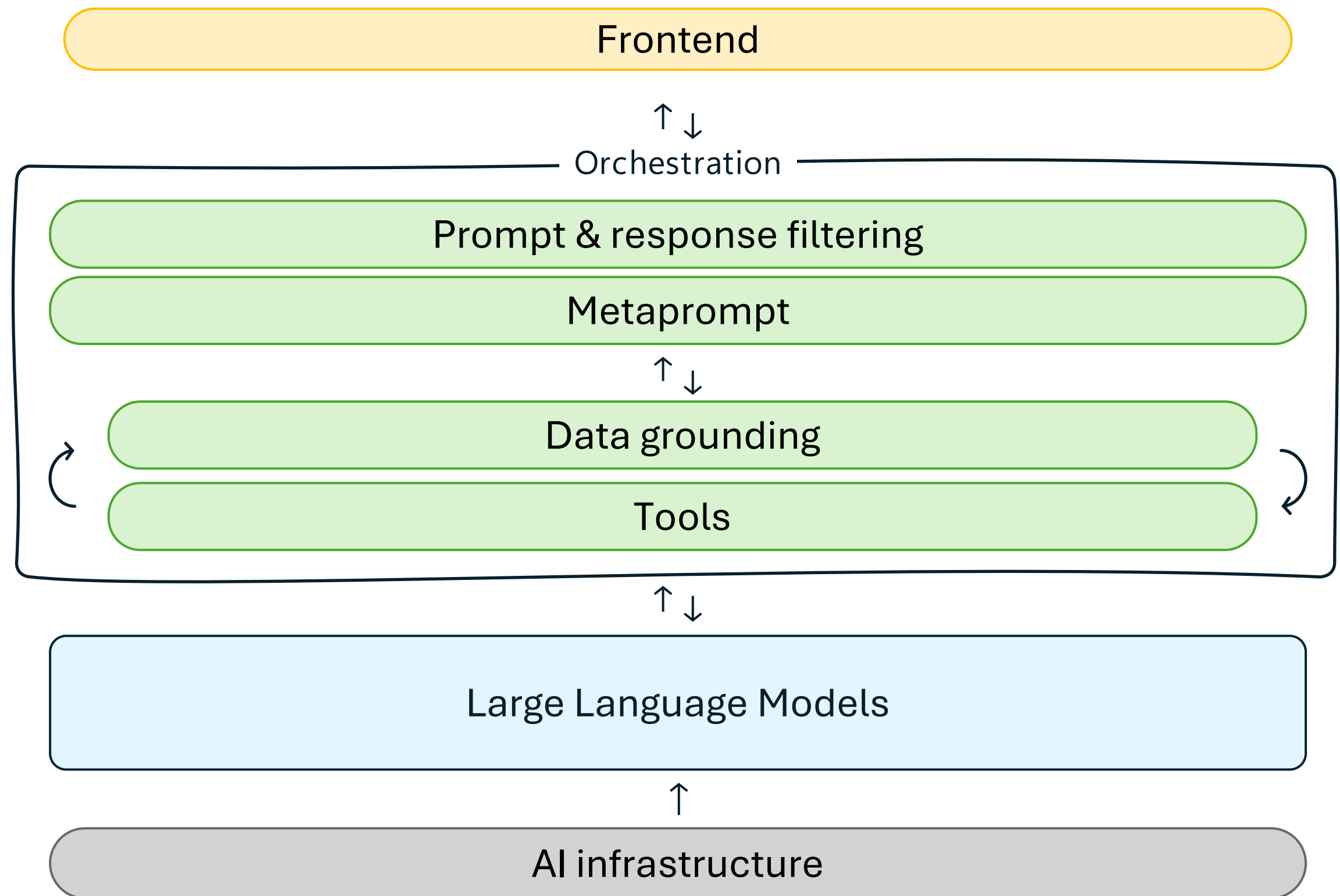
# LLMs as “brains” for our applications

Conversational  
Front-end



# Anatomy of an LLM-powered application

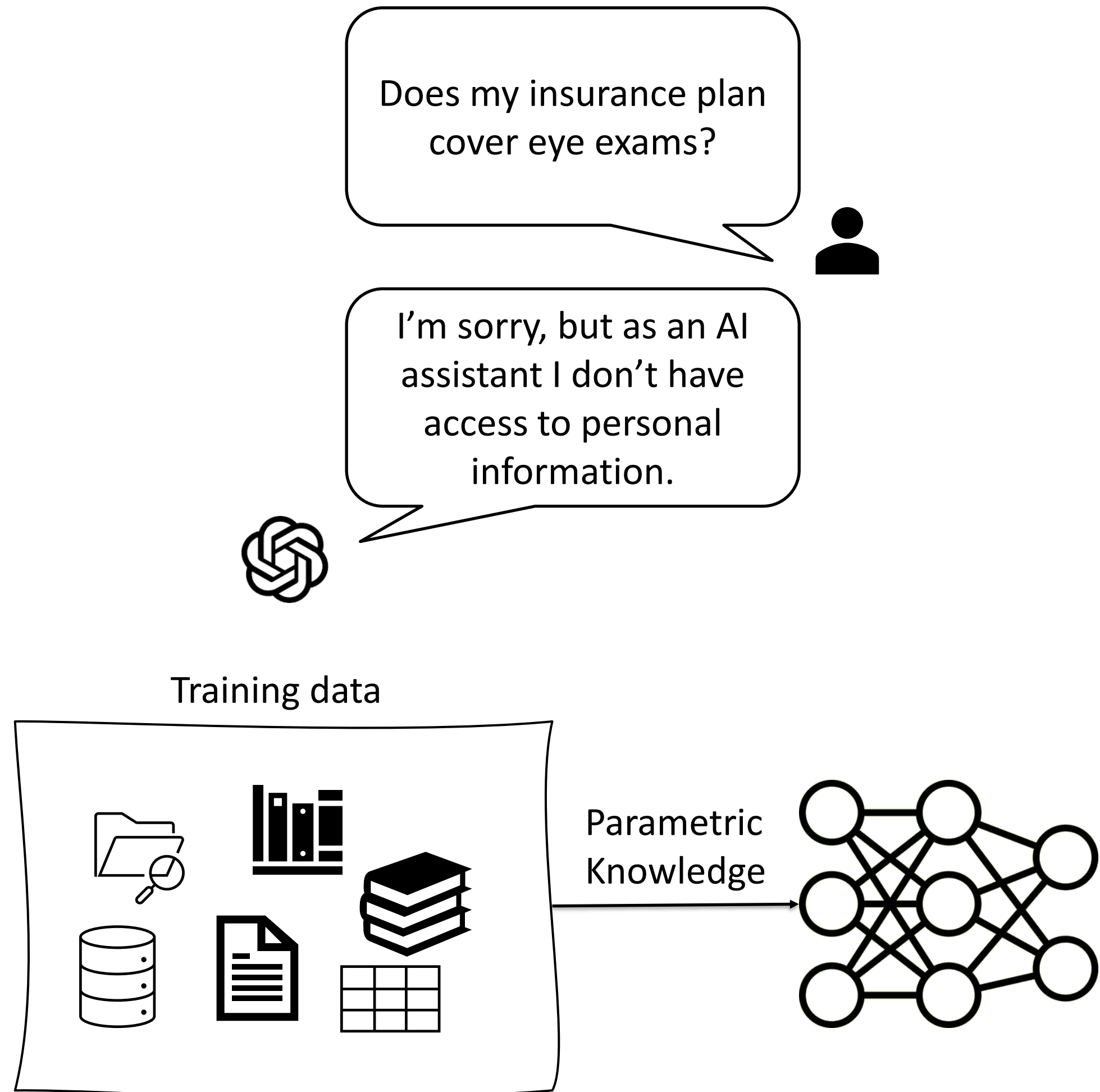
LLM-powered applications  
open the way to a new  
landscape of components



## Problem: Generative AI doesn't know about your data

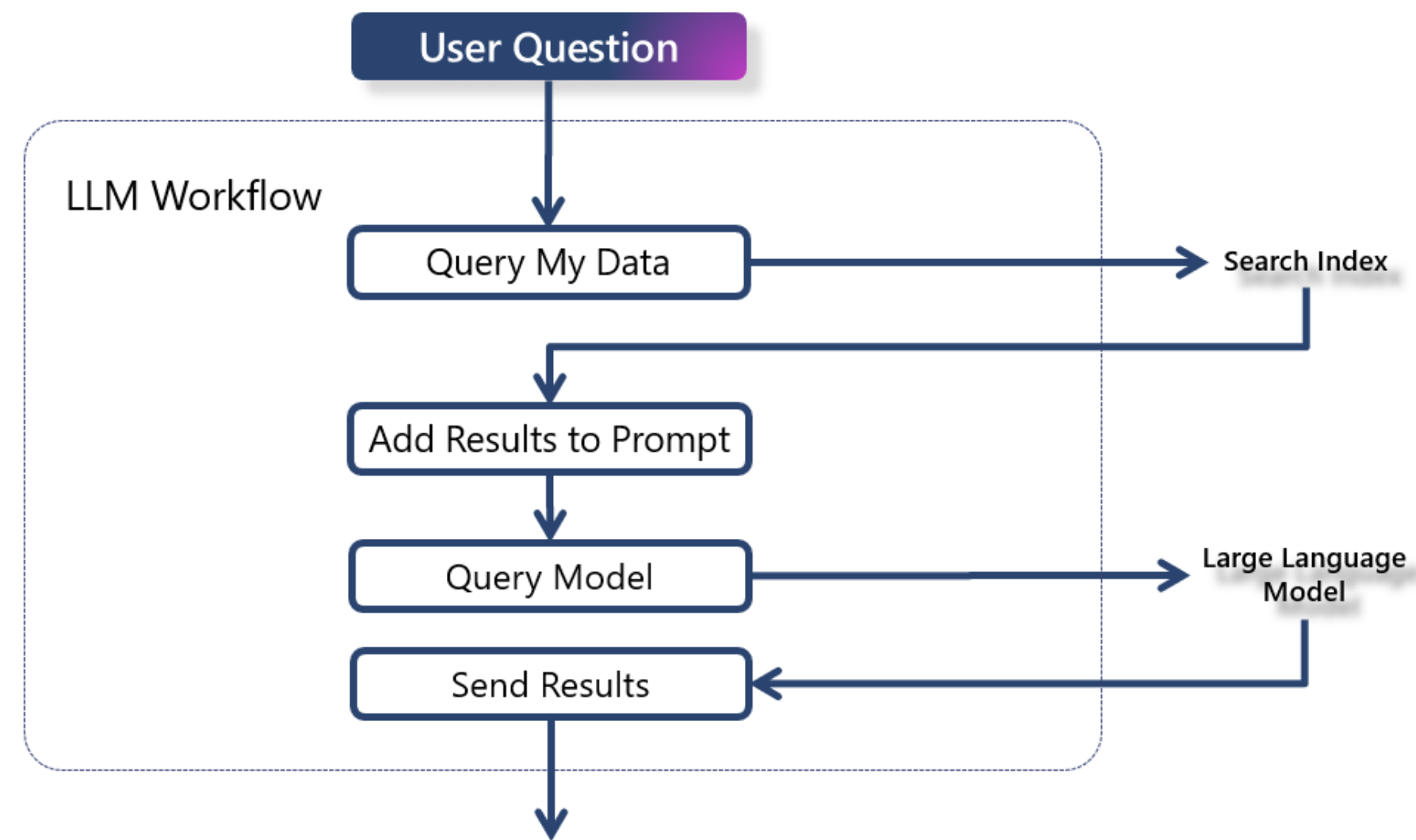
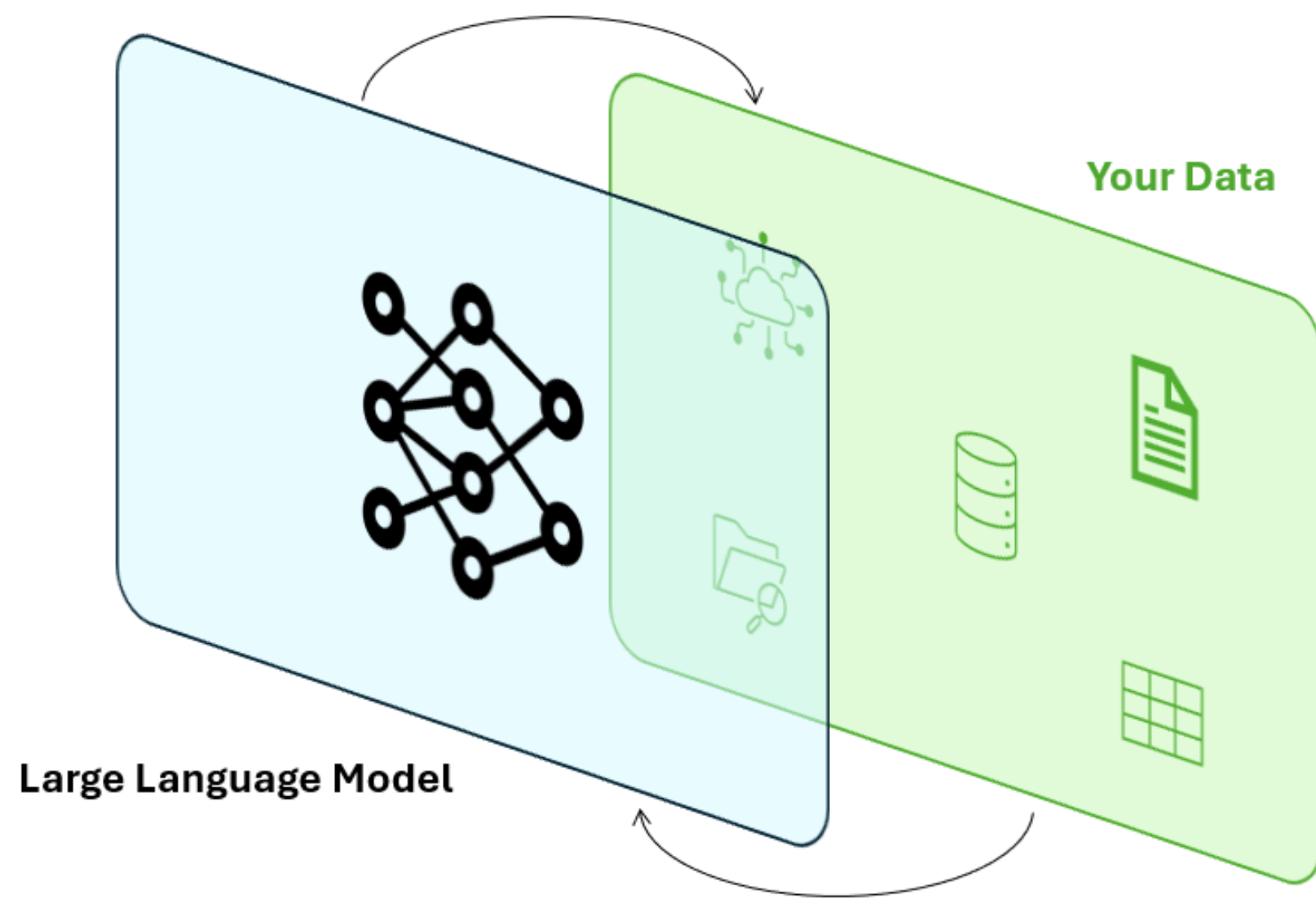
What if data you are interested in are not part of the training dataset?

- Personal Data (confidential, not public...)
- Up to date data
- Application data

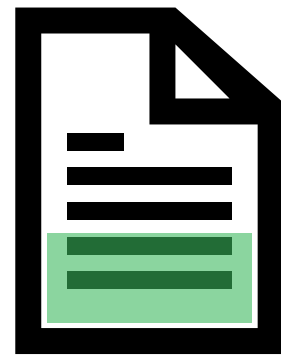
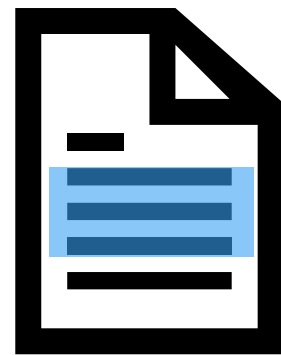




# Introducing Retrieval Augmented Generation



# Retrieval



Context

Tips for beginners:  
start...

Pegasus Shoe 123: best  
experience...

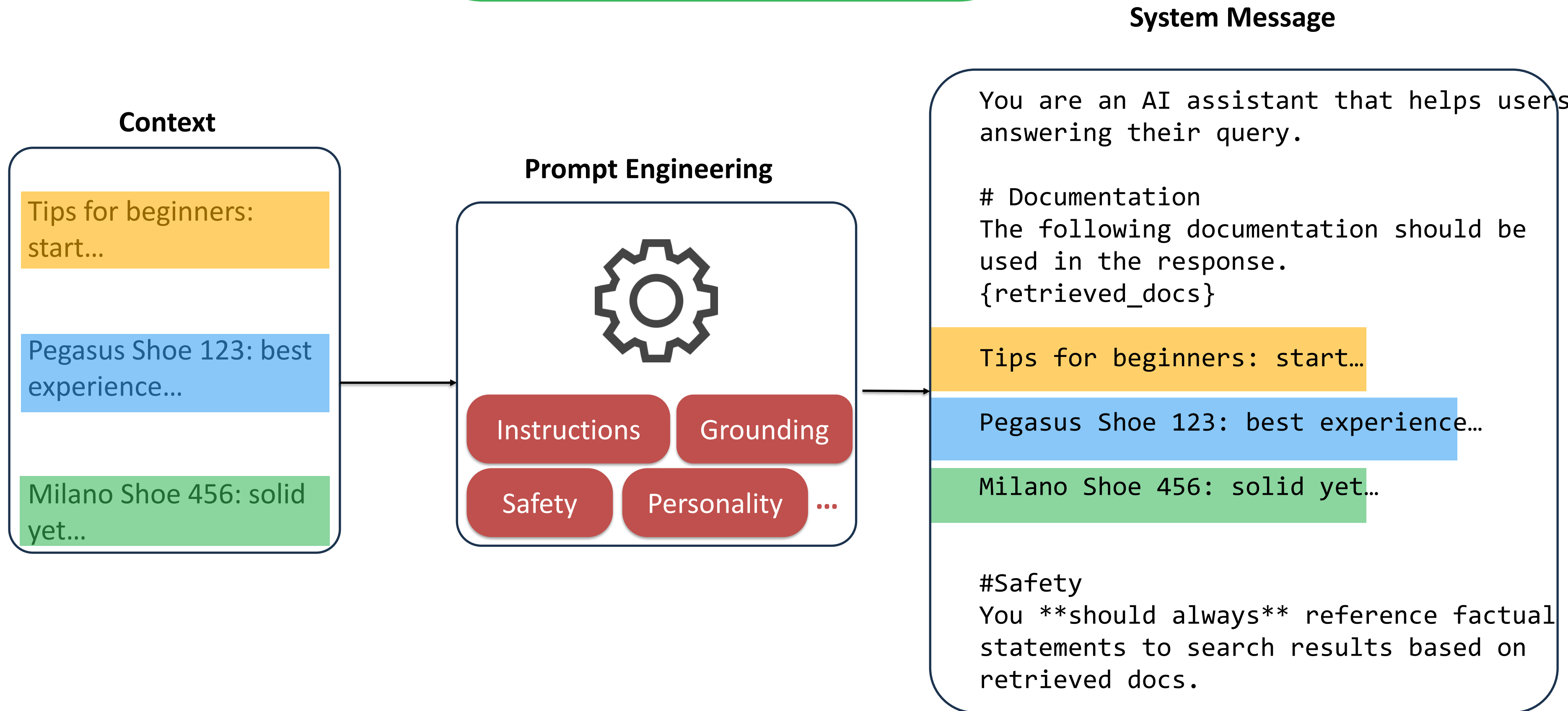
Milano Shoe 456: solid  
yet...

What is the best  
equipment for  
beginner climbers?





# Augmentation



# Generation

## System message + retrieved documents

You are an AI assistant that helps users answering their query.

# Documentation

The following documentation should be used in the response.

{retrieved\_docs}

Tips for beginners: start...

Pegasus Shoe 123: best experience...

Milano Shoe 456: solid yet...

#Safety

You **\*\*should always\*\*** reference factual statements to search results based on retrieved docs.



## User's query

What is the best equipment for beginner climbers?



Generative Model  
(e.g. GPT-4)



“According to the catalogue, if you are about to start climbing...”





How do we retrieve relevant documents?

*<3d style illustration of two cats playing a card game, one cat holding the deck of cards, the other cat thinking about which card to draw from the deck>*



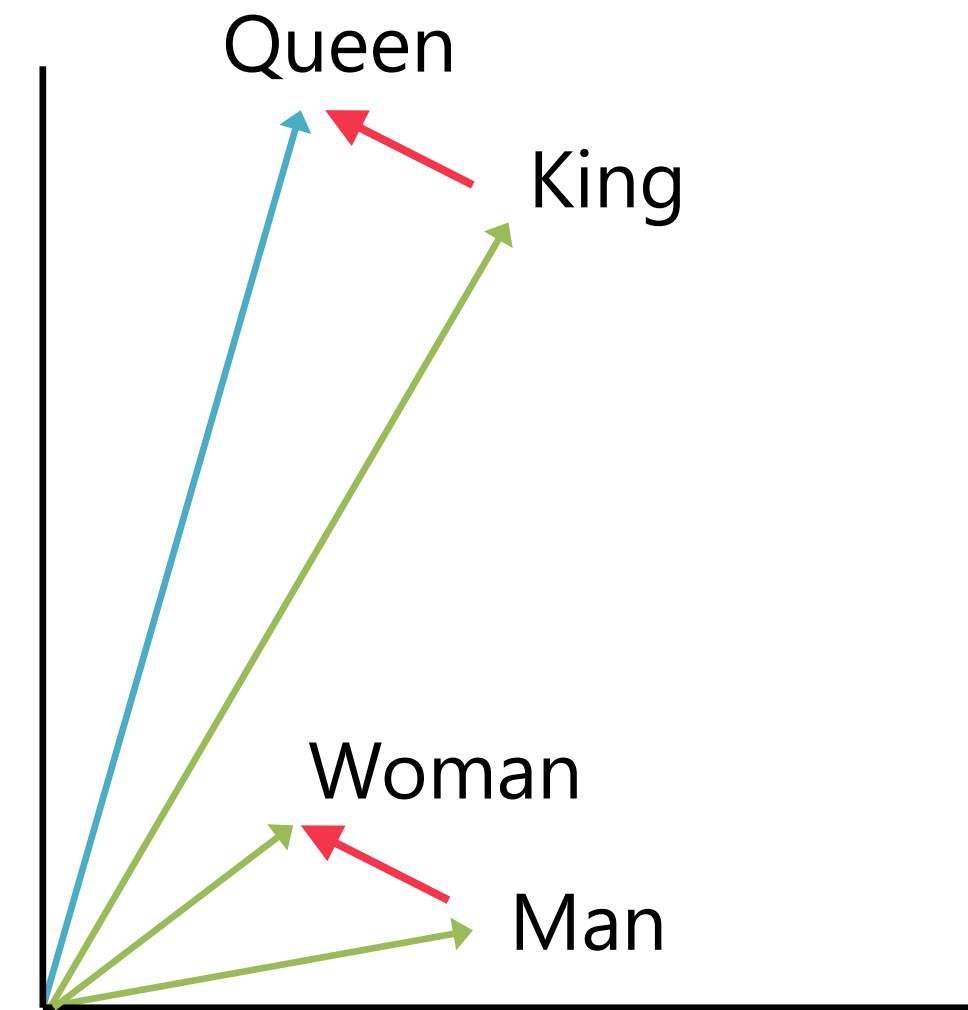
# Embedding – 1/4

An embedding is a way of representing high-dimensional, non-numeric data, such as words or sentences, in a lower-dimensional space, such as vector.

A text embedding can capture the semantic and syntactic features of the text, such as meaning, context, and similarity.

Each embedding is a vector of floating-point numbers, such that the distance between two embeddings in the vector space is correlated with semantic similarity between two inputs in the original format.

For example, if two concepts are similar, then their vector representations should also be similar.

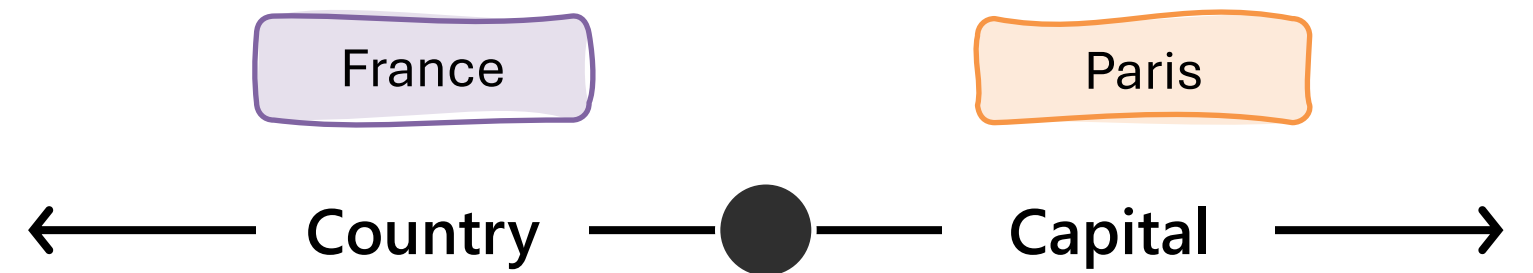


King-Man+Woman  $\approx$  Queen



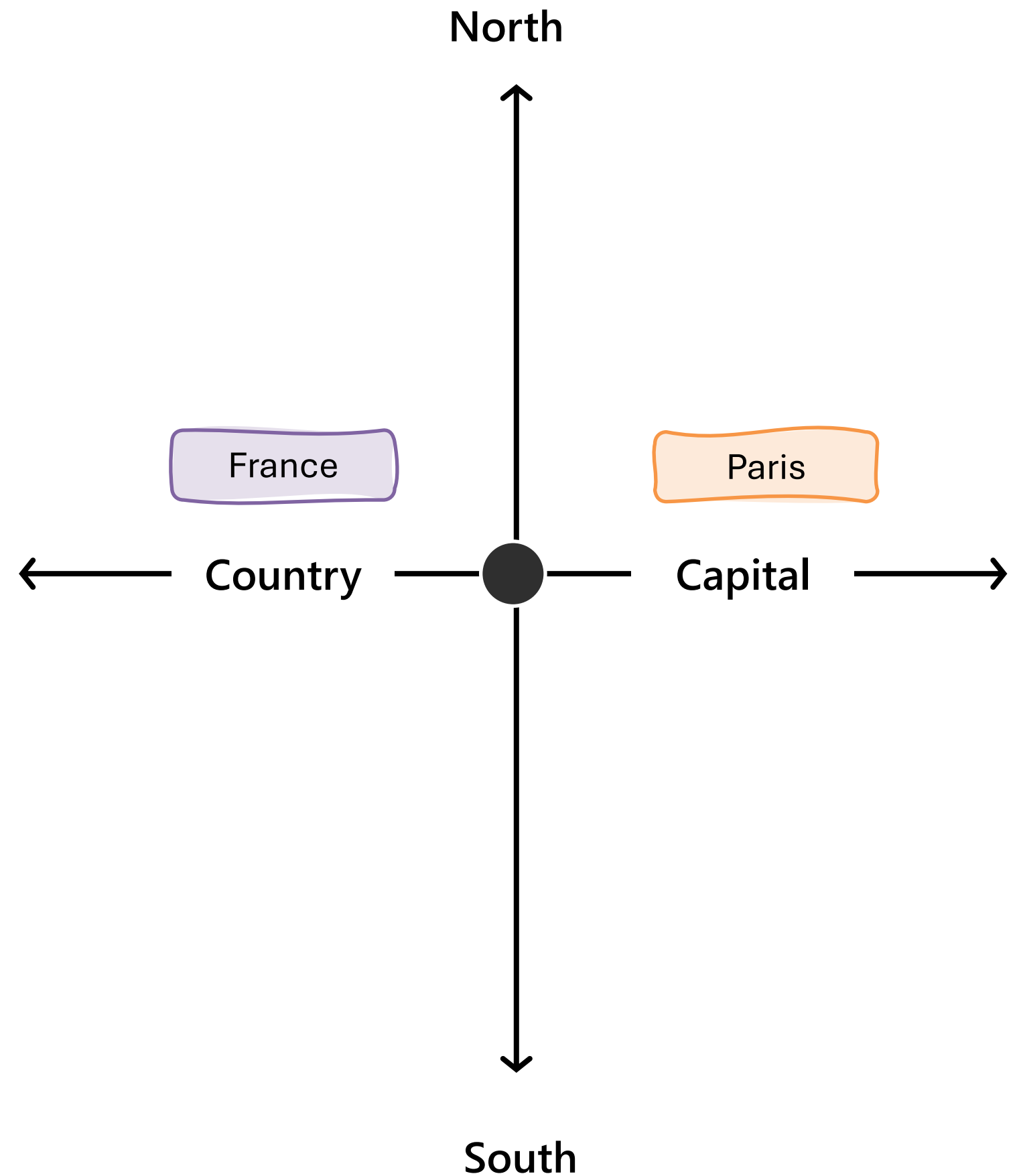
## Embedding – 1/4

Embeddings represent your data, and each dimension represents a feature of that data.



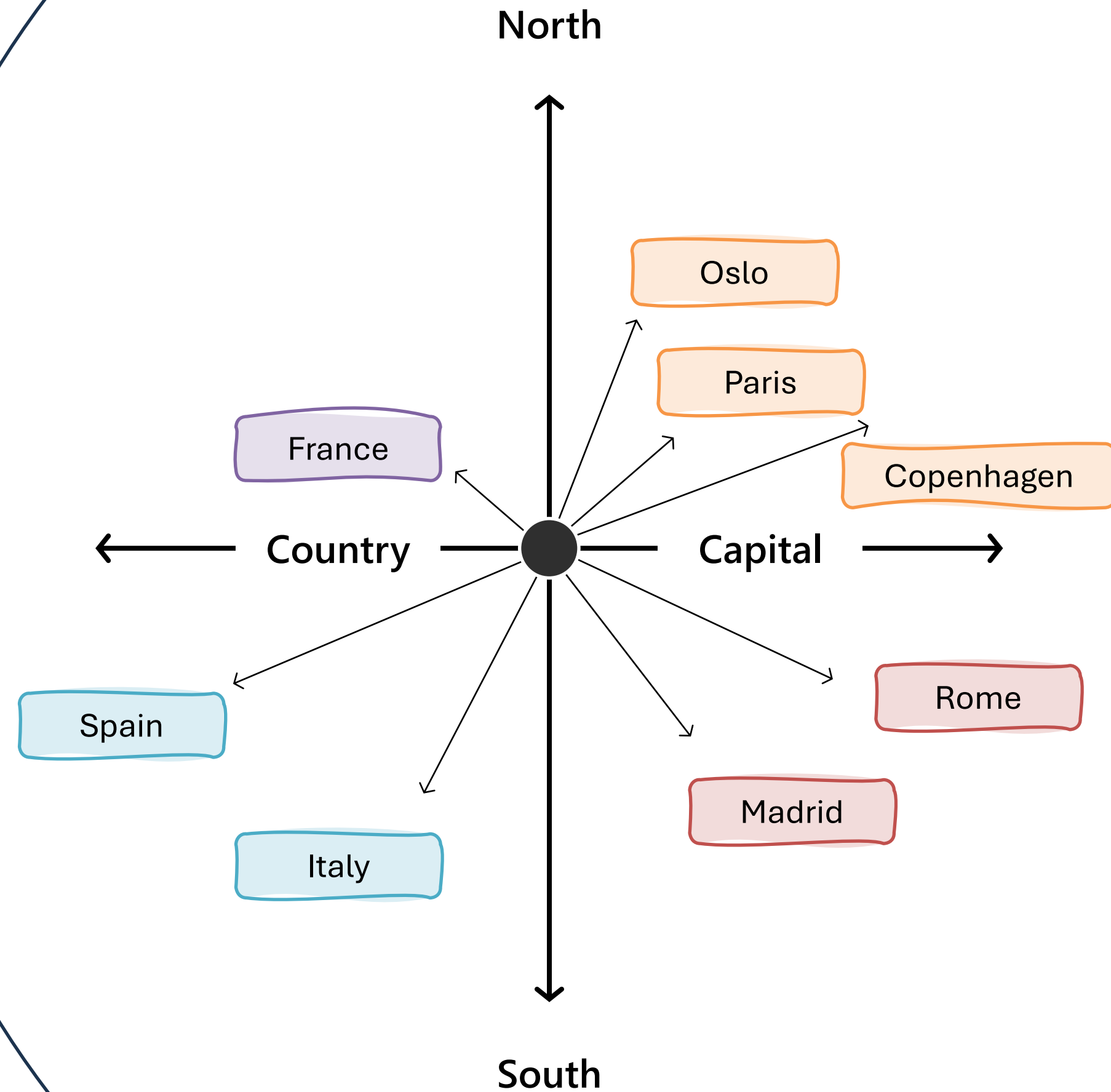
## Embedding – 3/4

For example, one dimension could be the geographic connotation (country vs capital), another one the geographic position (north vs south).



## Embedding – 4/4

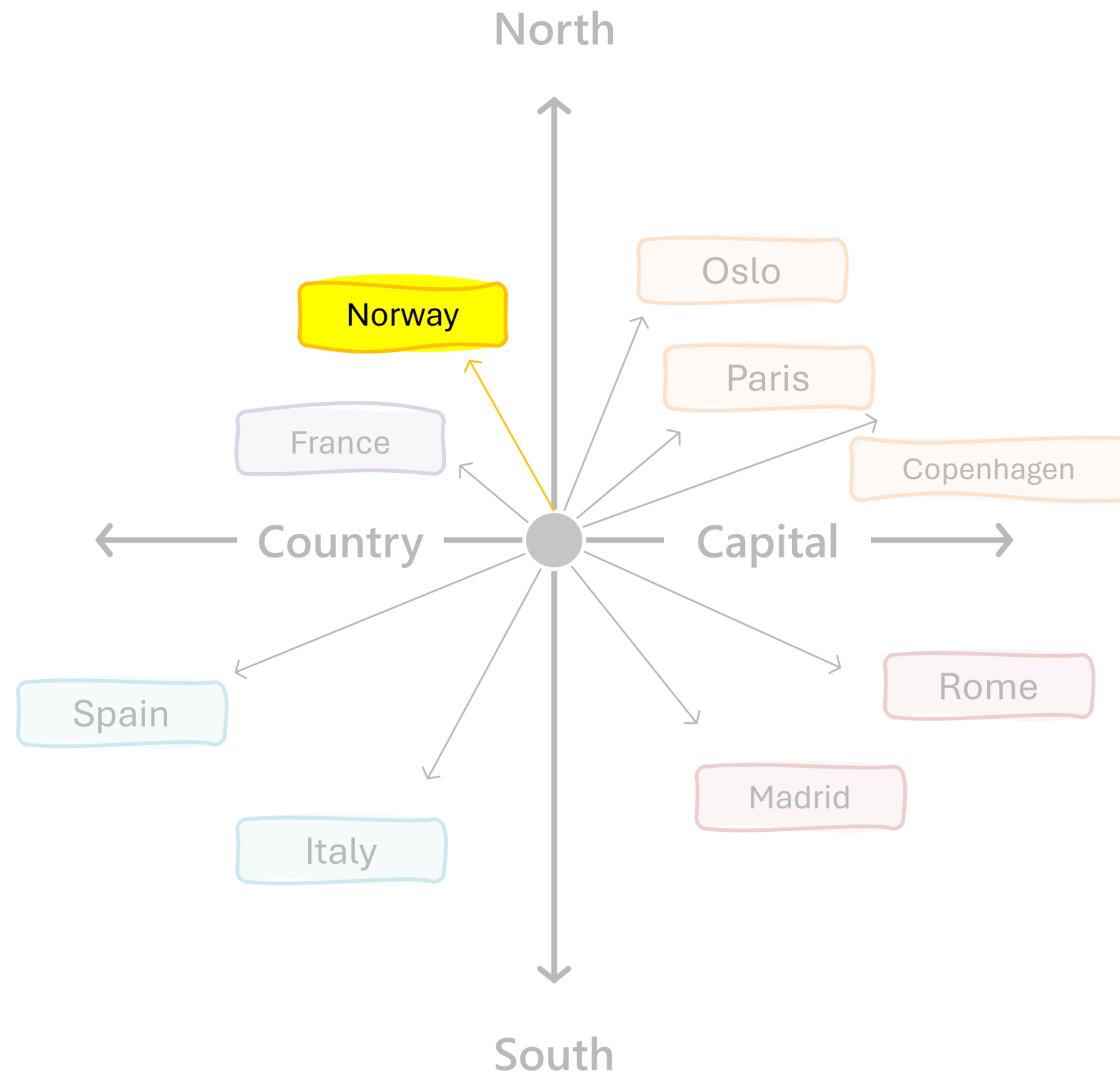
In the embedding space, similar concepts (words, sentences, documents) should be close in mathematical distance.



Vector search ranks objects by similarity (relevance) to the query



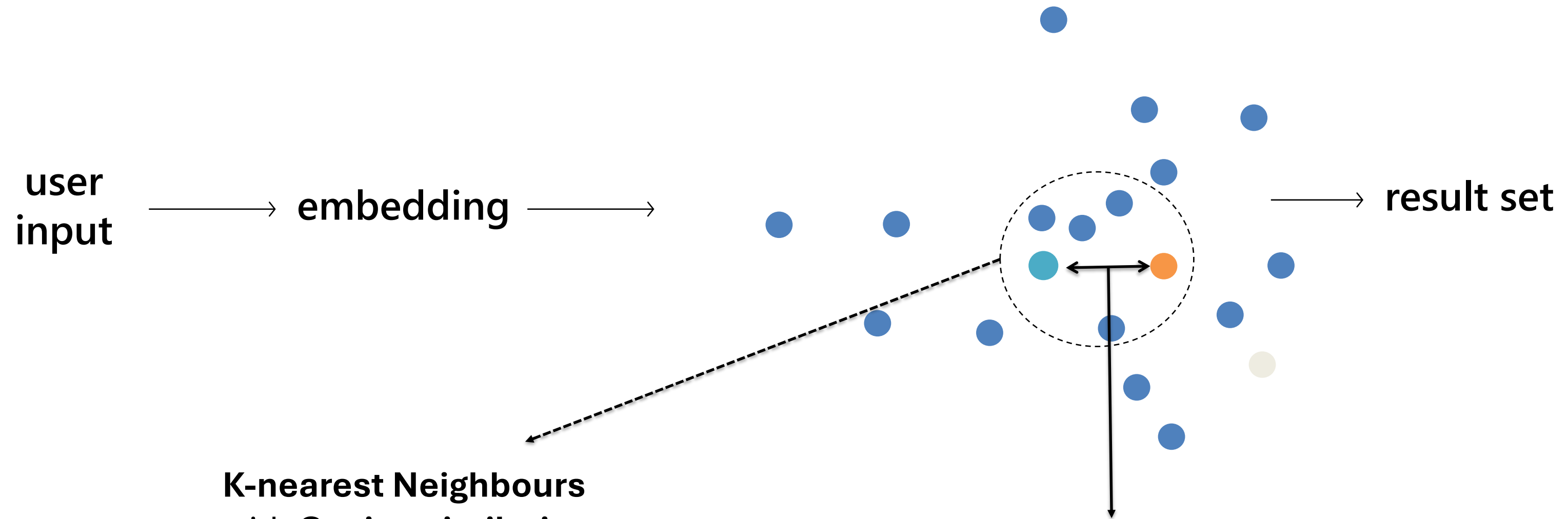
**Norway**



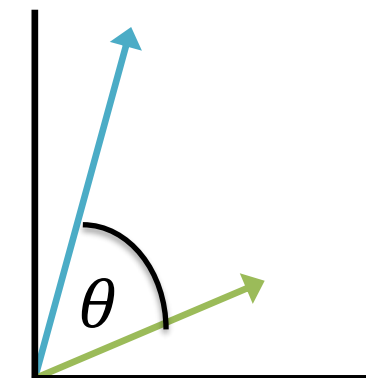
Relevance	Result
Query	Norway
1	France
2	Oslo
3	Copenhagen
4	...



# Similarity Search with Embeddings



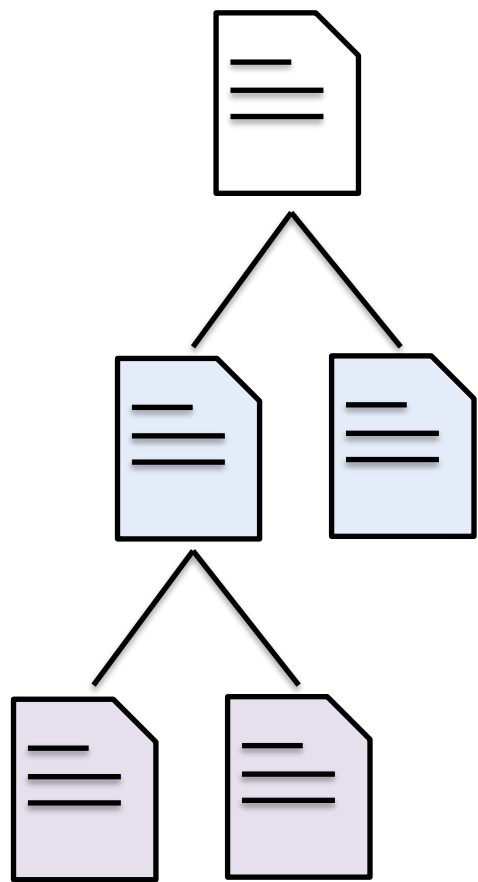
**K-nearest Neighbours**  
with **Cosine similarity**  
distance



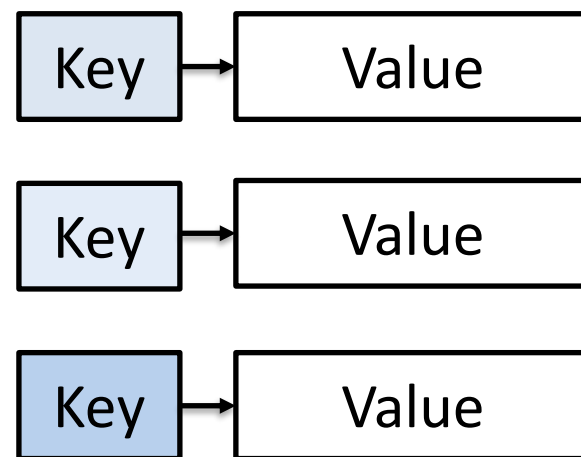
$$\cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|} = \frac{\sum_{i=1}^n A_i B_i}{\sqrt{\sum_{i=1}^n A_i^2} \sqrt{\sum_{i=1}^n B_i^2}}$$

# A new entry in the landscape of DB

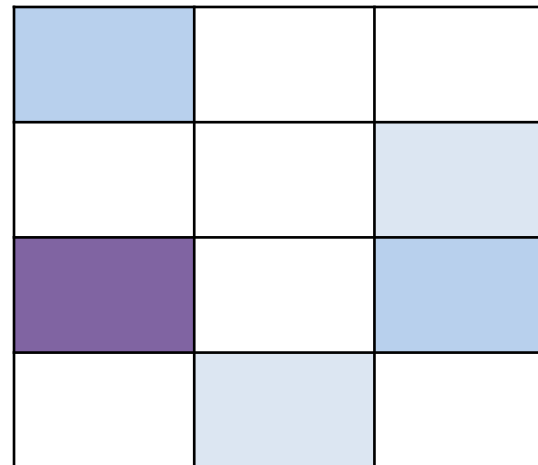
**Documents DB**



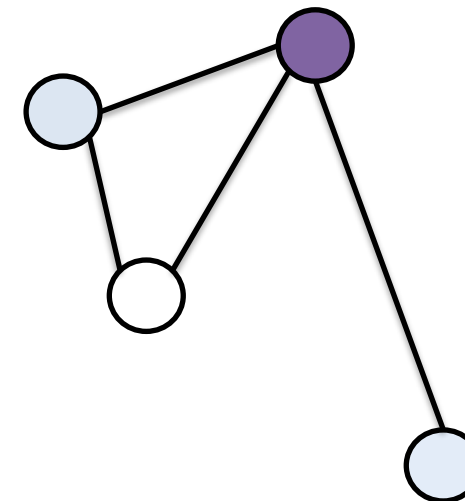
**Key-value DB**



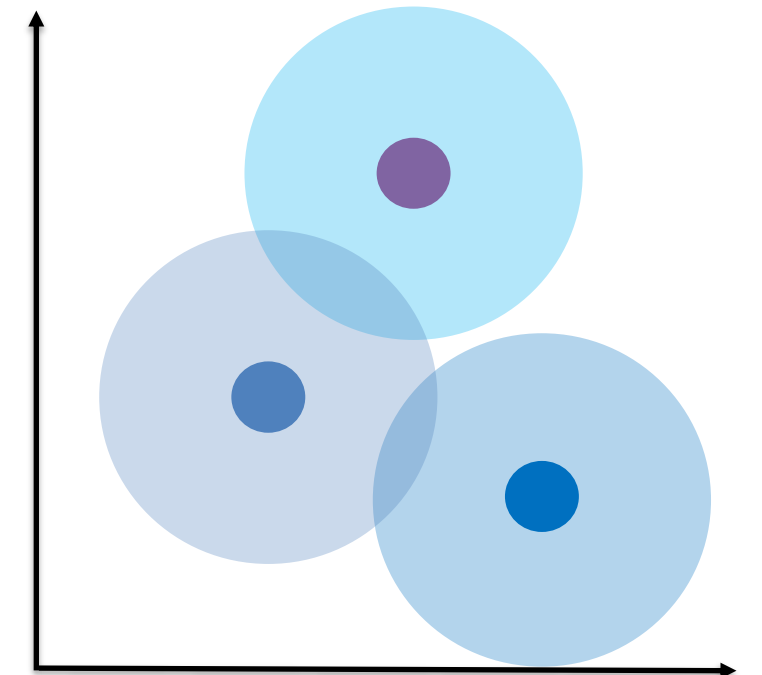
**Wide-columns DB**



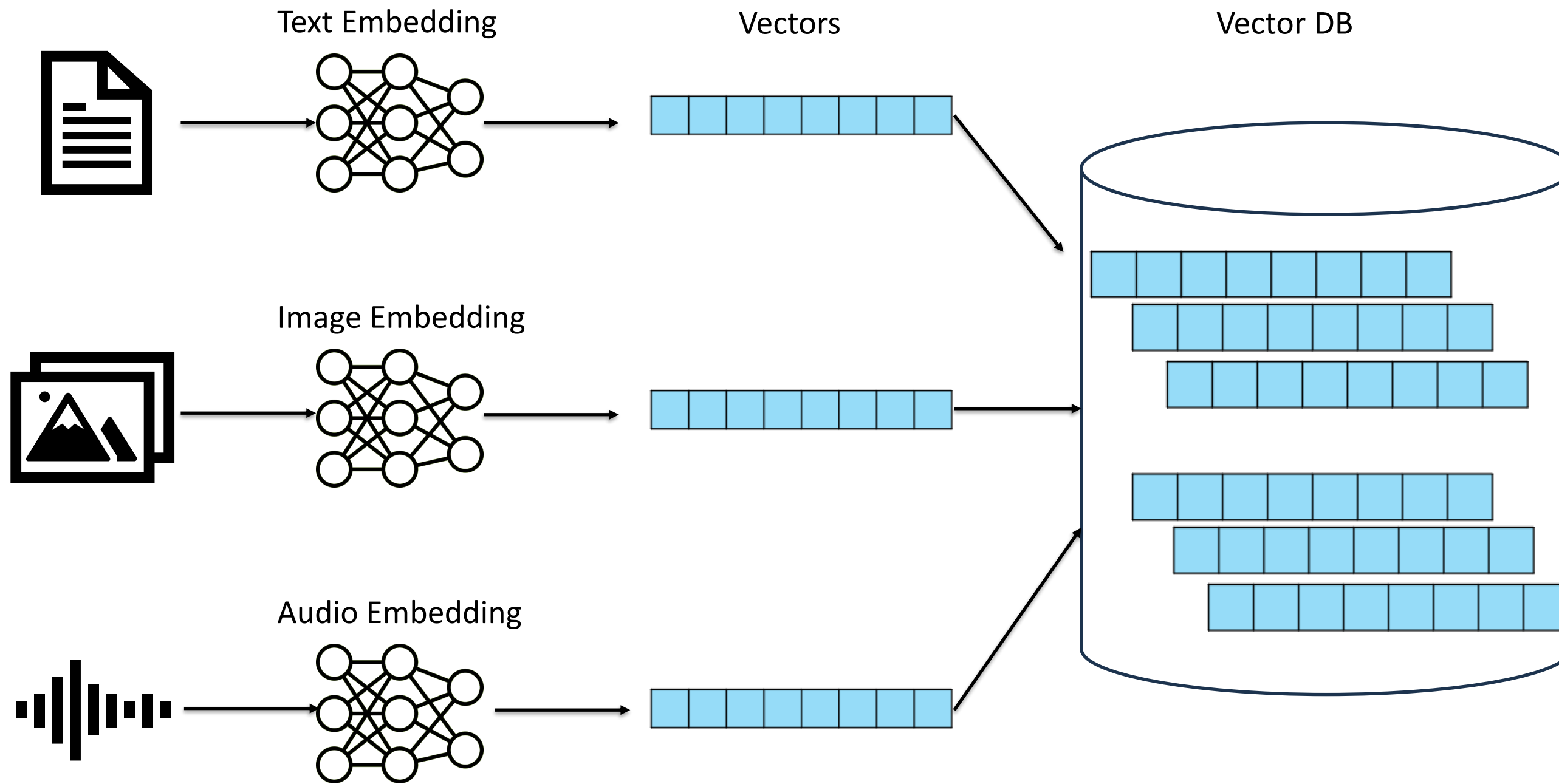
**Graph DB**



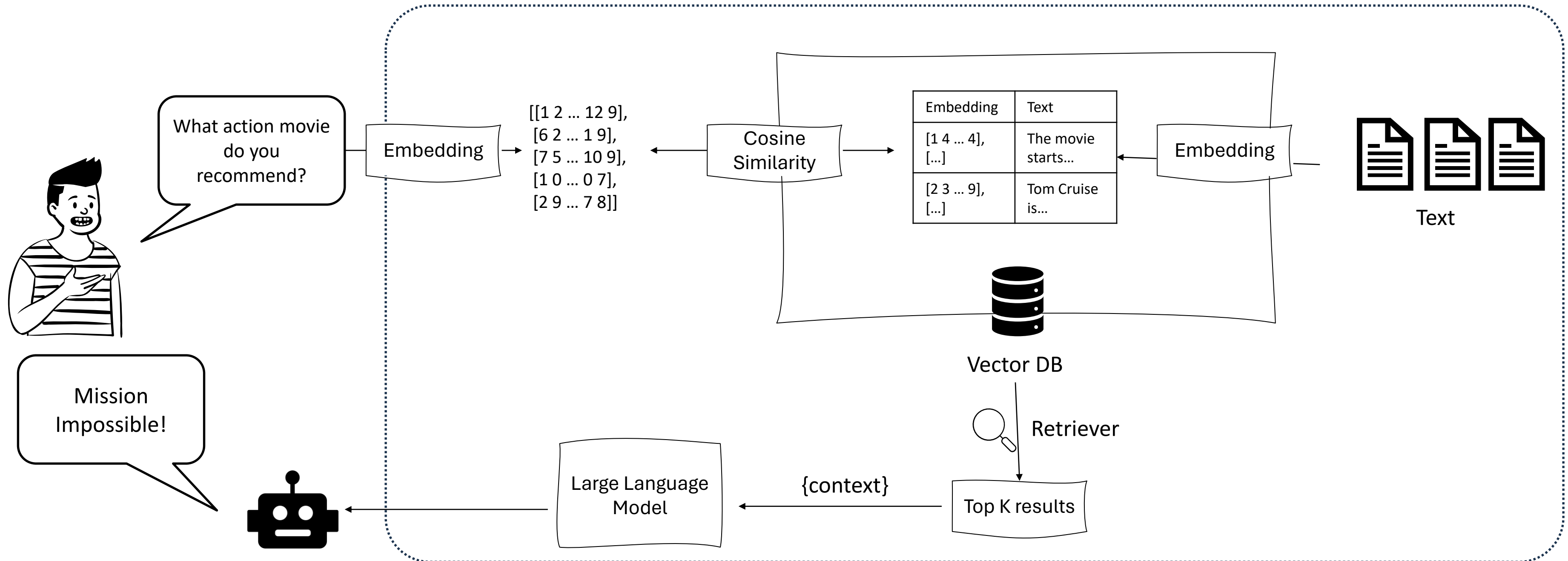
**Vector DB**



# Vector Databases



# Monomodal RAG (text only)



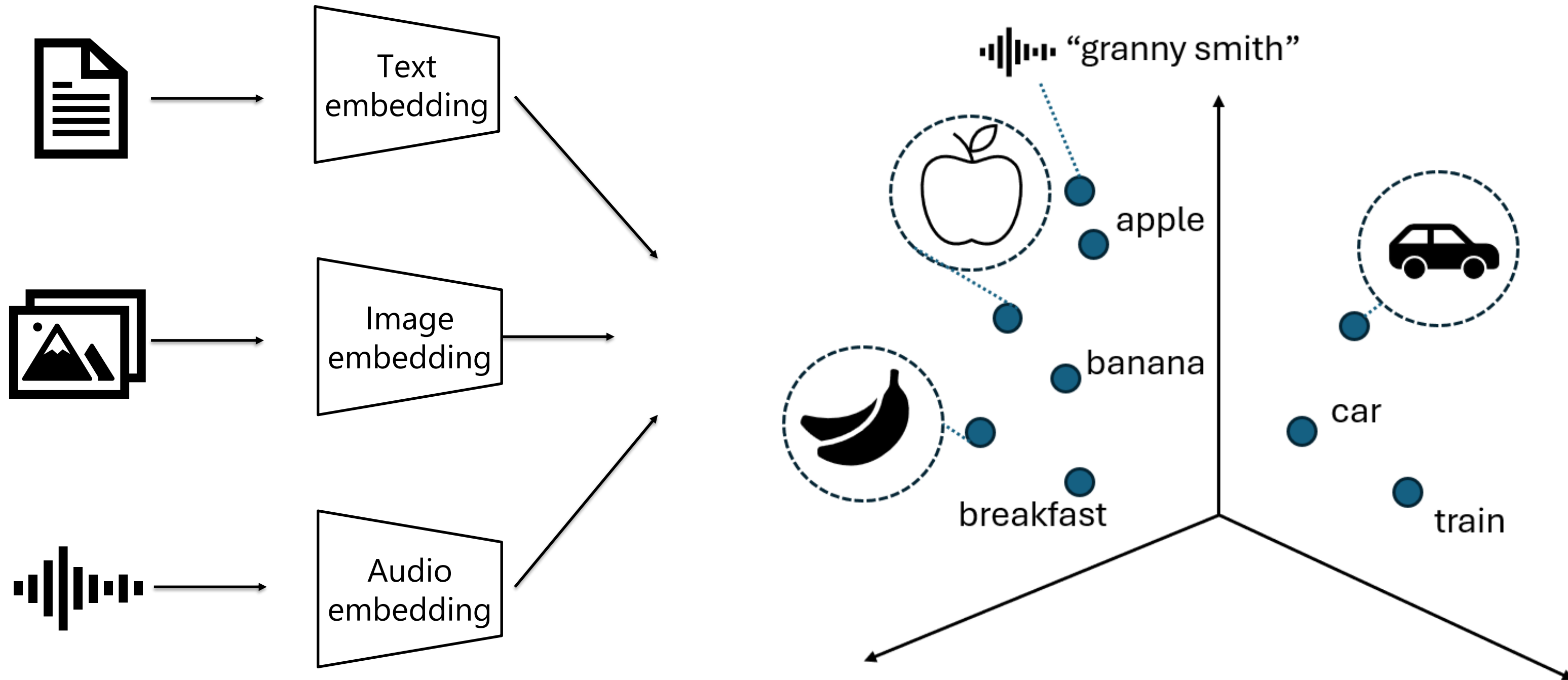


**Humans  
communicate in  
multiple ways**

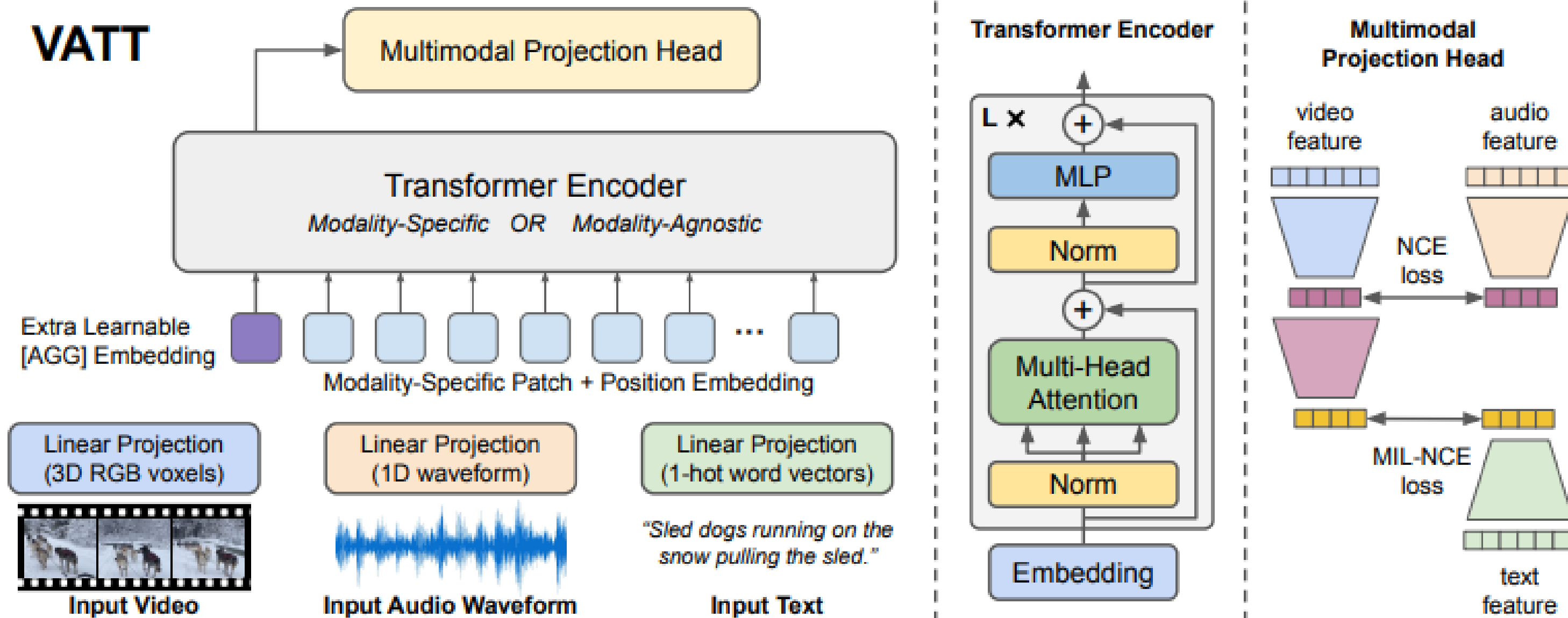




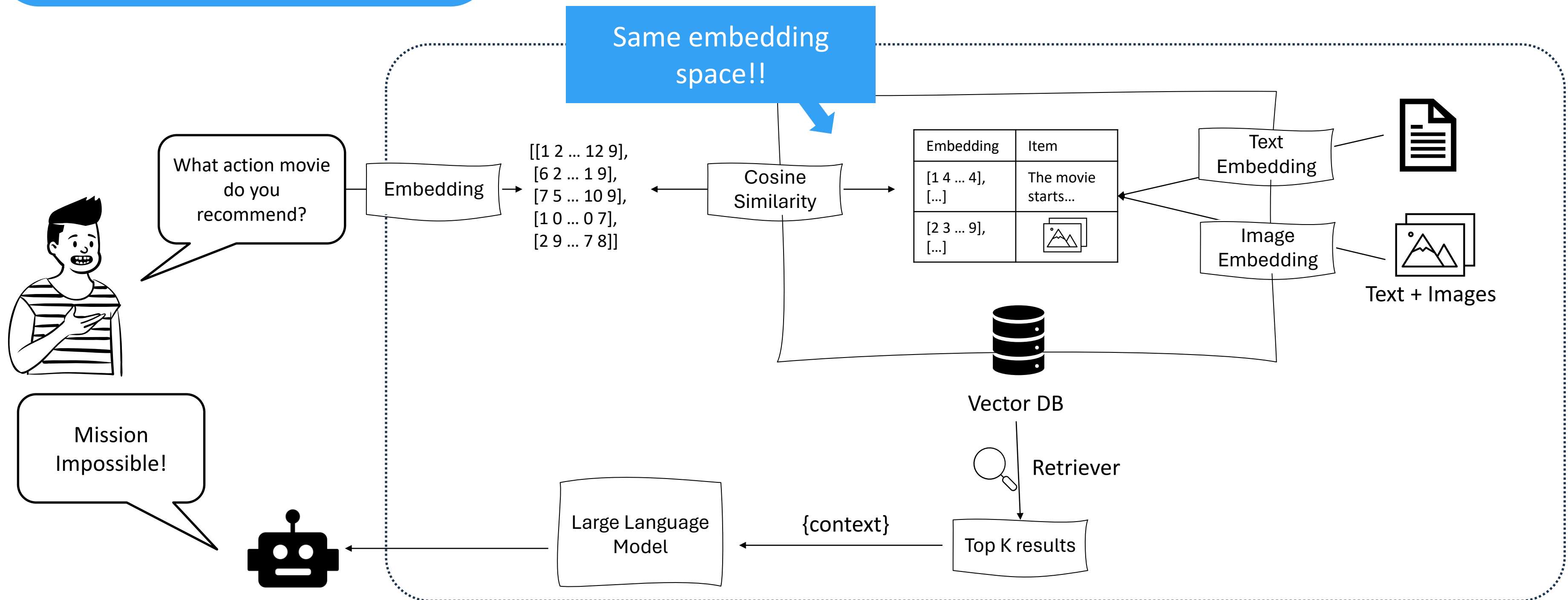
# Introducing Large Multimodal Models



# Example of Multimodality: VATT

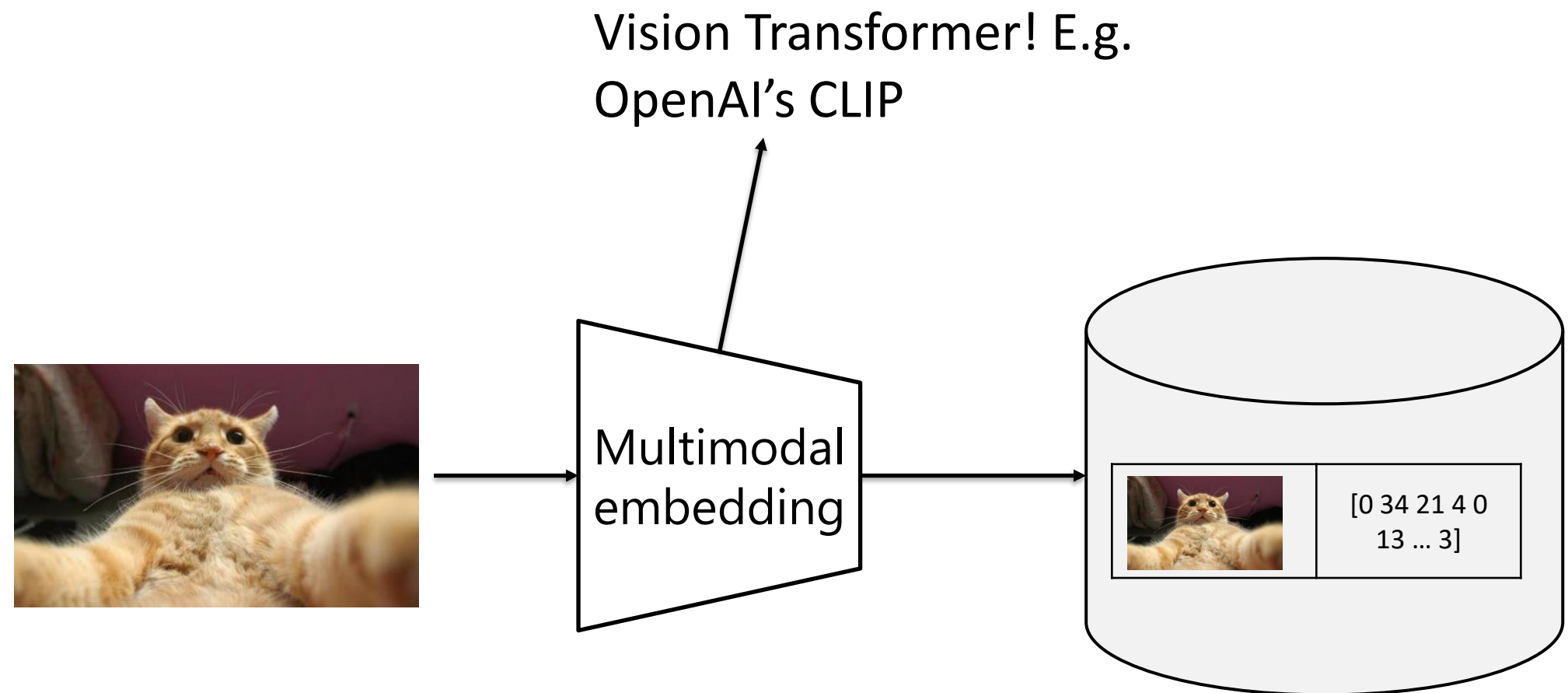


# Multimodal RAG (text + images)





Option 1: leverage  
an image  
embedding model



# Attention is all you need – once more

## AN IMAGE IS WORTH 16X16 WORDS: TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE

Alexey Dosovitskiy<sup>\*,†</sup>, Lucas Beyer<sup>\*</sup>, Alexander Kolesnikov<sup>\*</sup>, Dirk Weissenborn<sup>\*</sup>,  
Xiaohua Zhai<sup>\*</sup>, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer,  
Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, Neil Houlsby<sup>\*,†</sup>

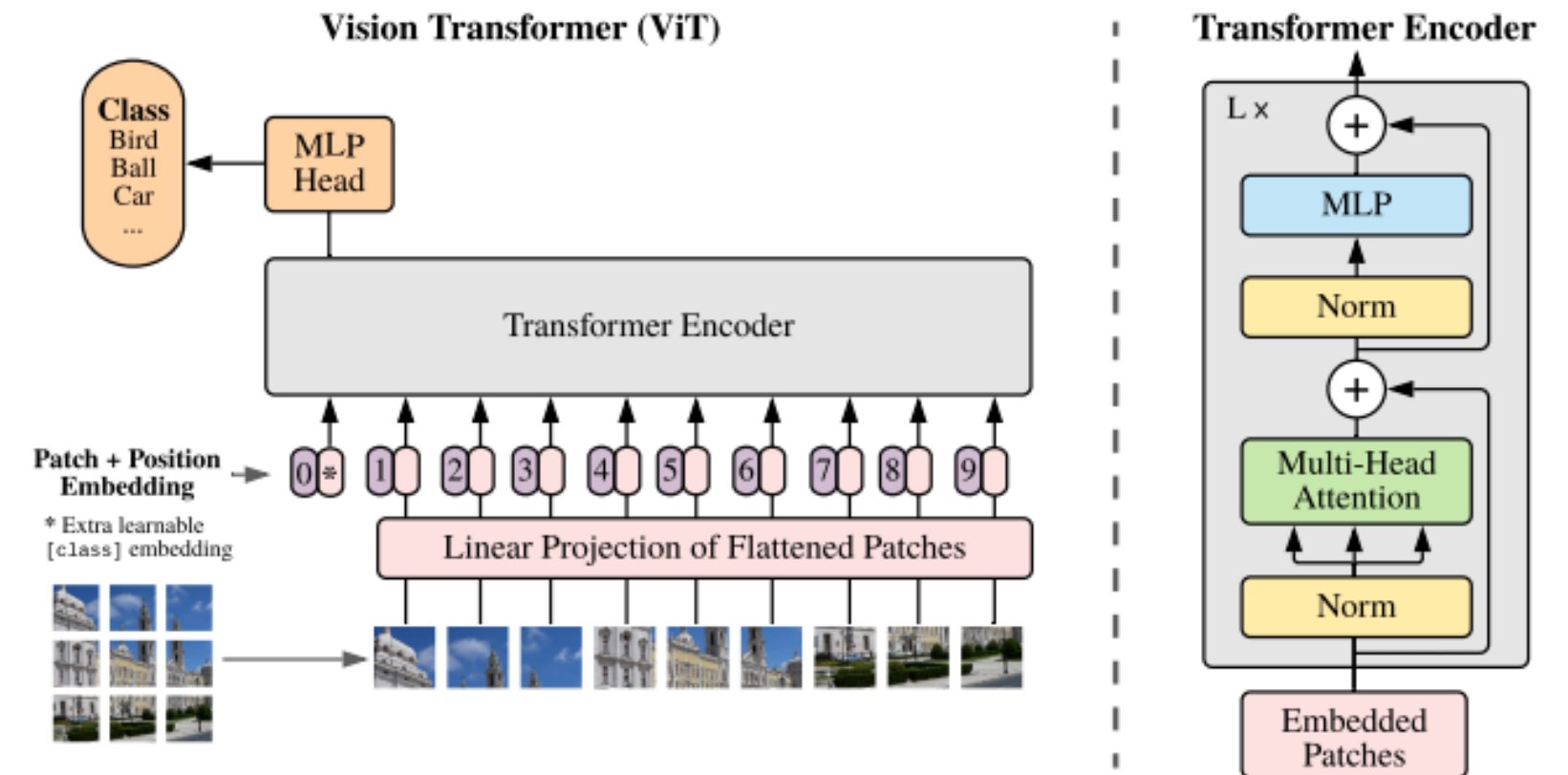
<sup>\*</sup>equal technical contribution, <sup>†</sup>equal advising

Google Research, Brain Team

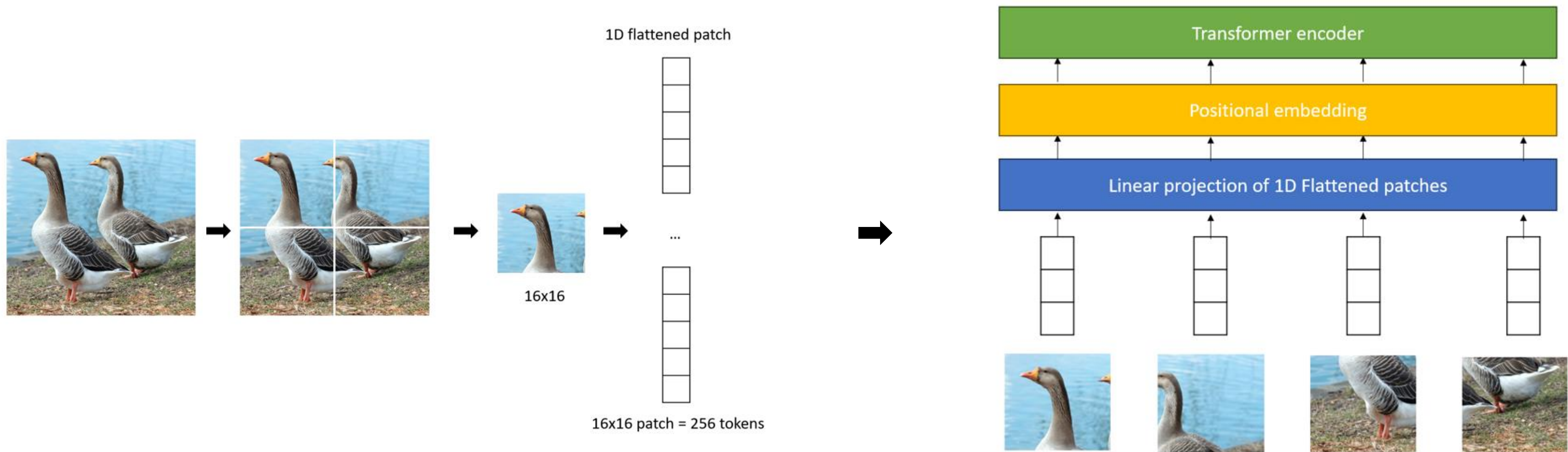
{adosovitskiy, neilhoulby}@google.com

### ABSTRACT

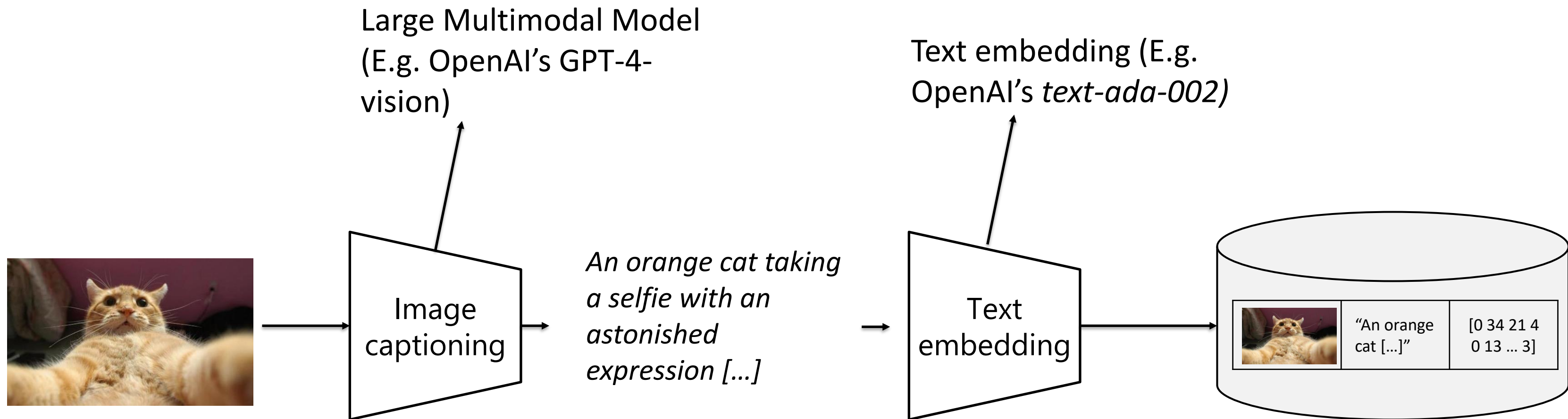
While the Transformer architecture has become the de-facto standard for natural language processing tasks, its applications to computer vision remain limited. In vision, attention is either applied in conjunction with convolutional networks, or used to replace certain components of convolutional networks while keeping their overall structure in place. We show that this reliance on CNNs is not necessary and a pure transformer applied directly to sequences of image patches can perform very well on image classification tasks. When pre-trained on large amounts of data and transferred to multiple mid-sized or small image recognition benchmarks (ImageNet, CIFAR-100, VTAB, etc.), Vision Transformer (ViT) attains excellent results compared to state-of-the-art convolutional networks while requiring substantially fewer computational resources to train.<sup>1</sup>



# Breaking down images into patches

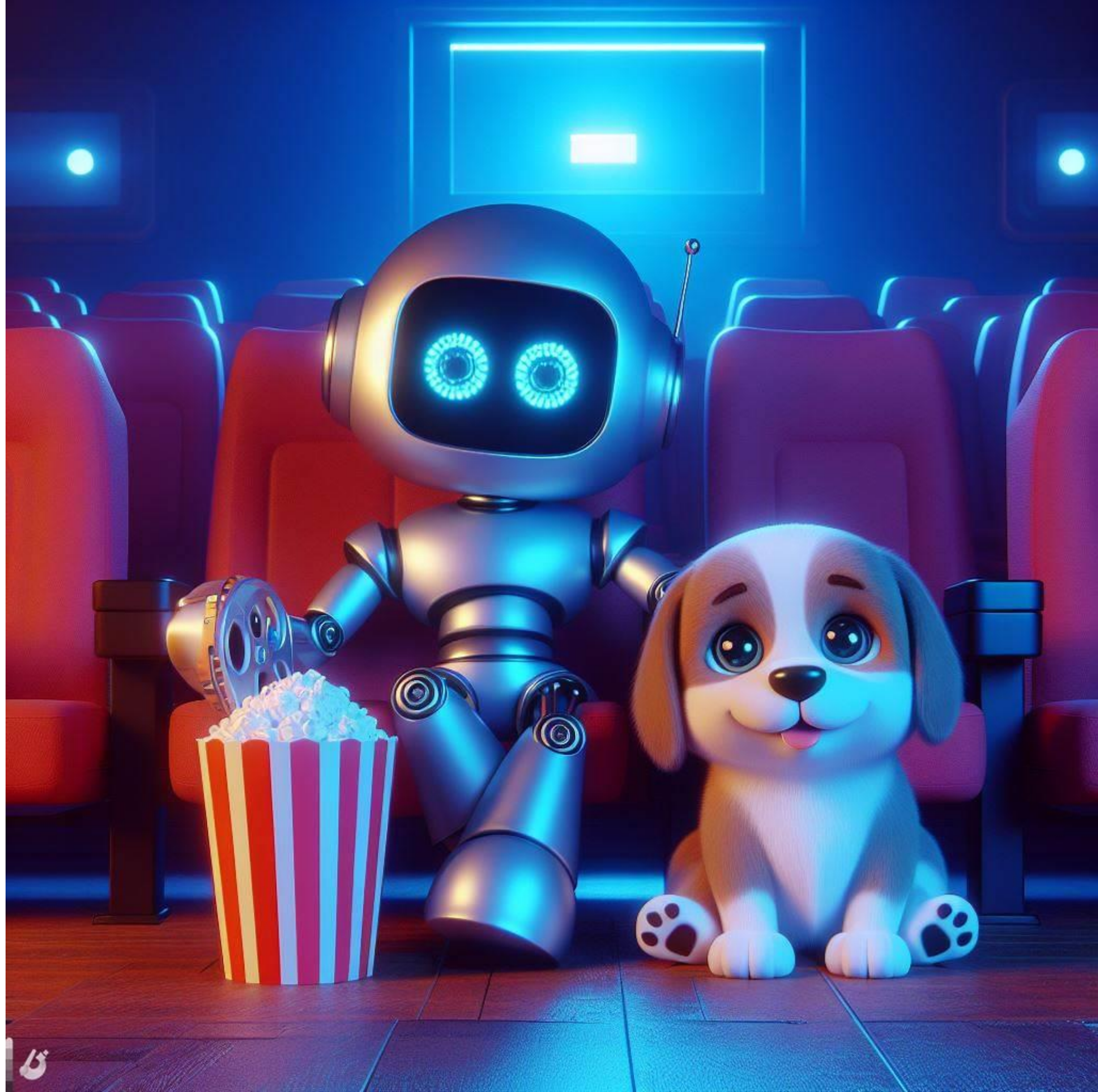


## Option 2: Using an LMM to generate images embeddings



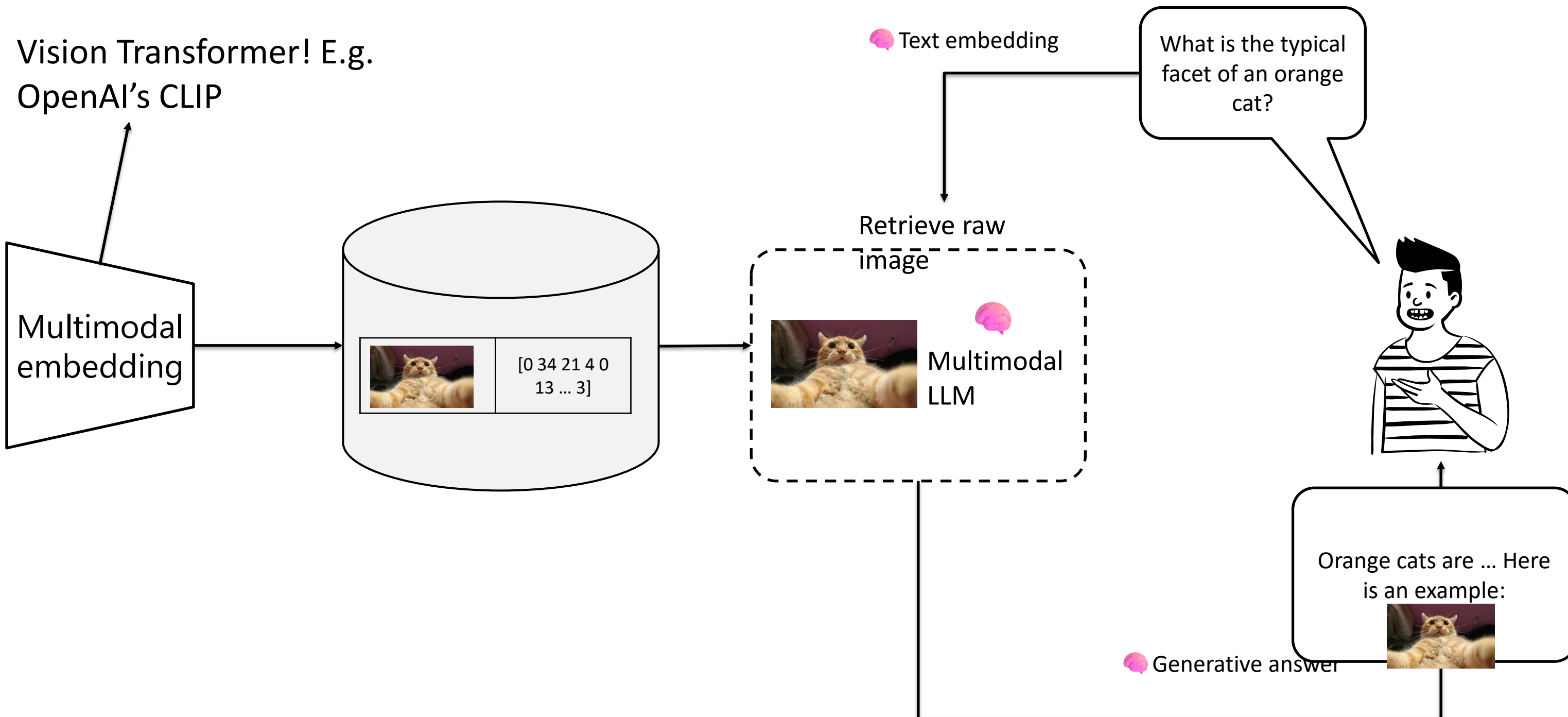


Demo Time!





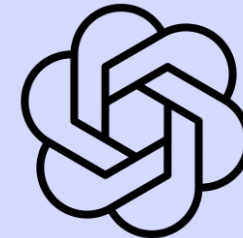
# Option 1: Image embeddings + text embeddings



## Our Ingredients



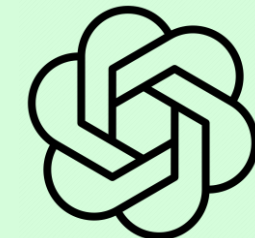
### MODELS



GPT-4  
GPT4-TURBO-  
VISION



### EMBEDDING



CLIP  
TEXT-  
EMBEDDING-  
ADA-002



### VECTORDB



QDRANT



### ORCHESTRATOR



LLAMA-INDEX

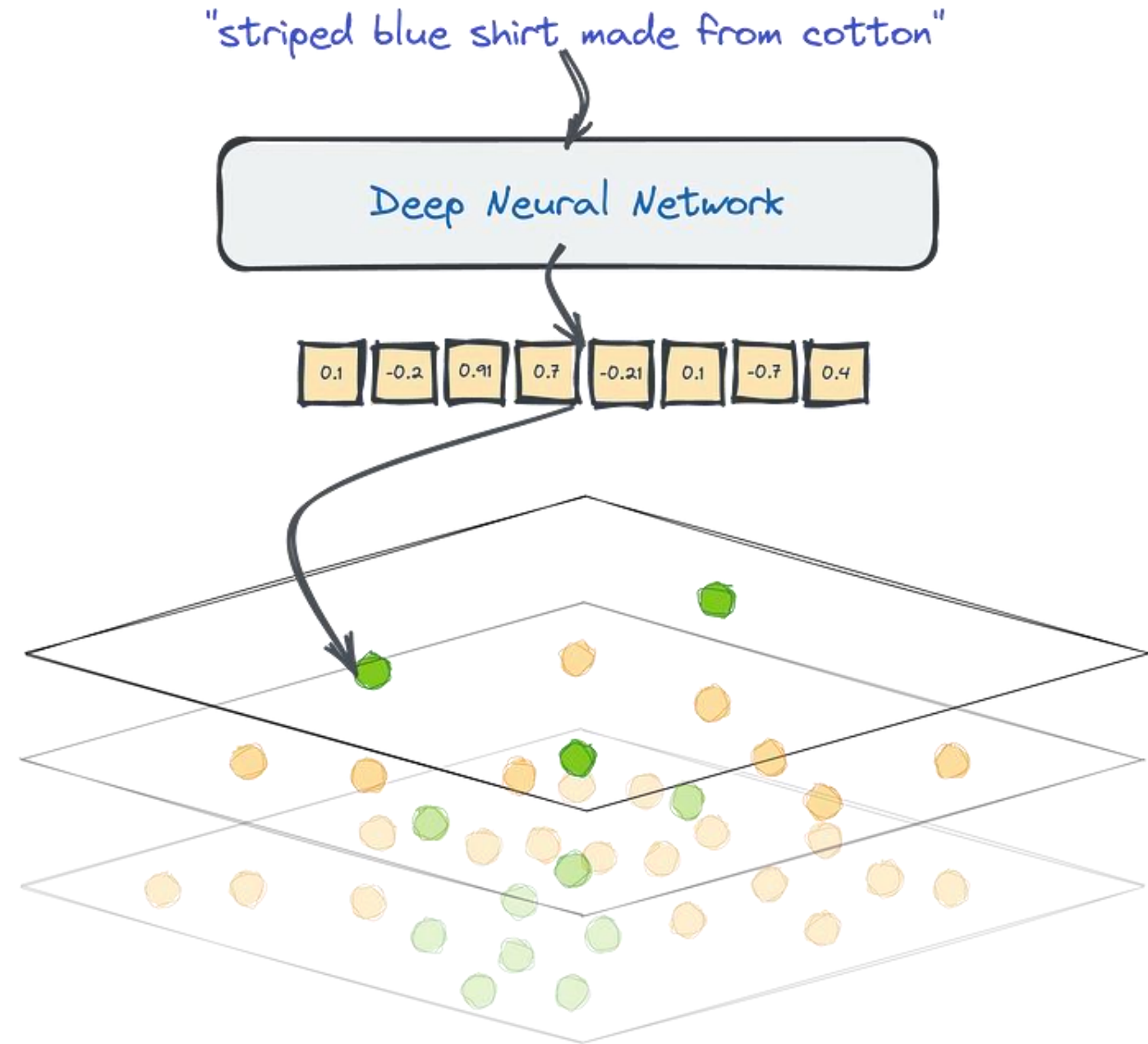
# Qdrant



**Challenge** → find similar documents in a big set of objects



**Solution** → using a graph-like structure to find the closest object, so that we compute the distance for some candidates only.

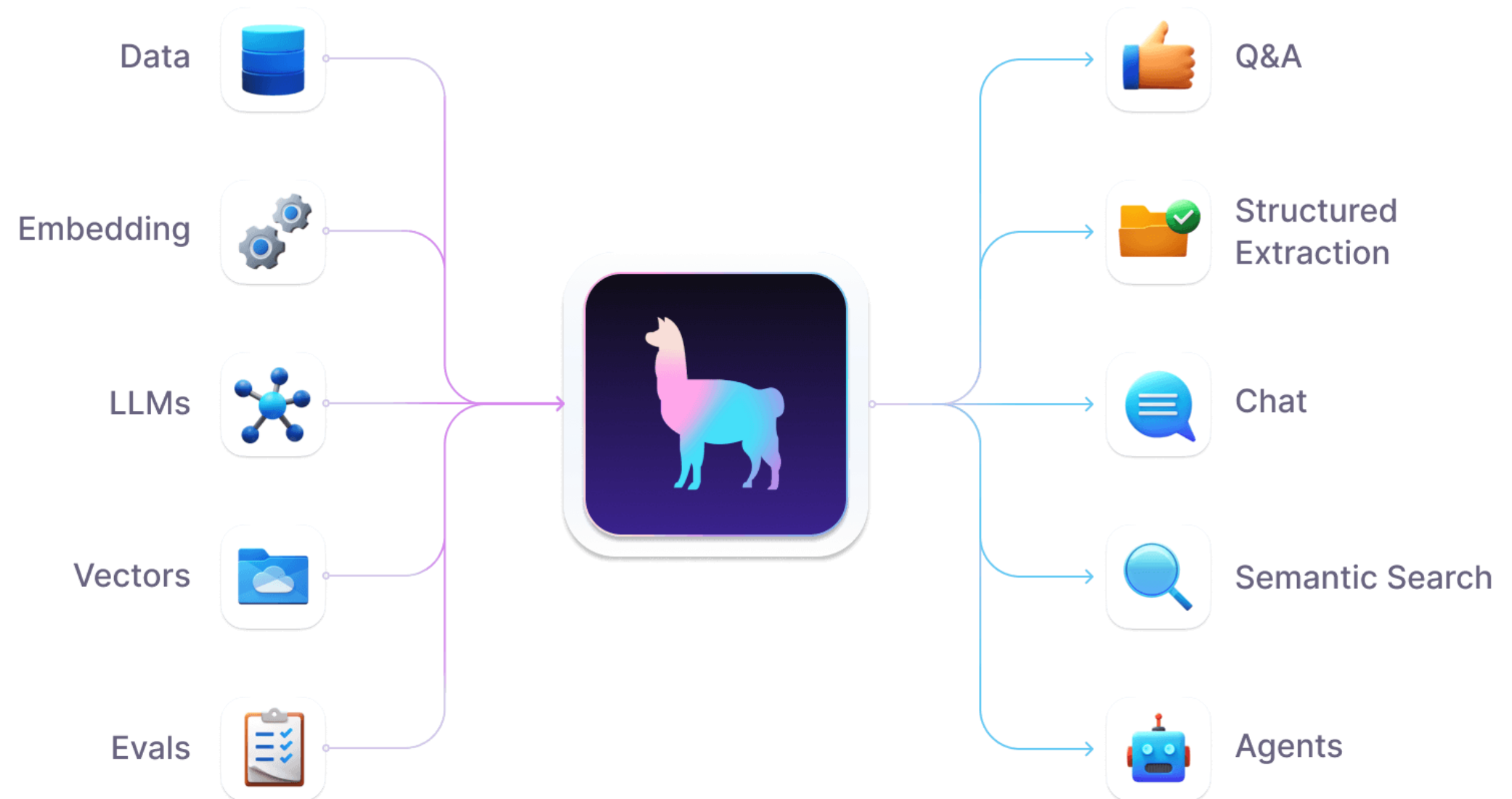


# Llama-Index

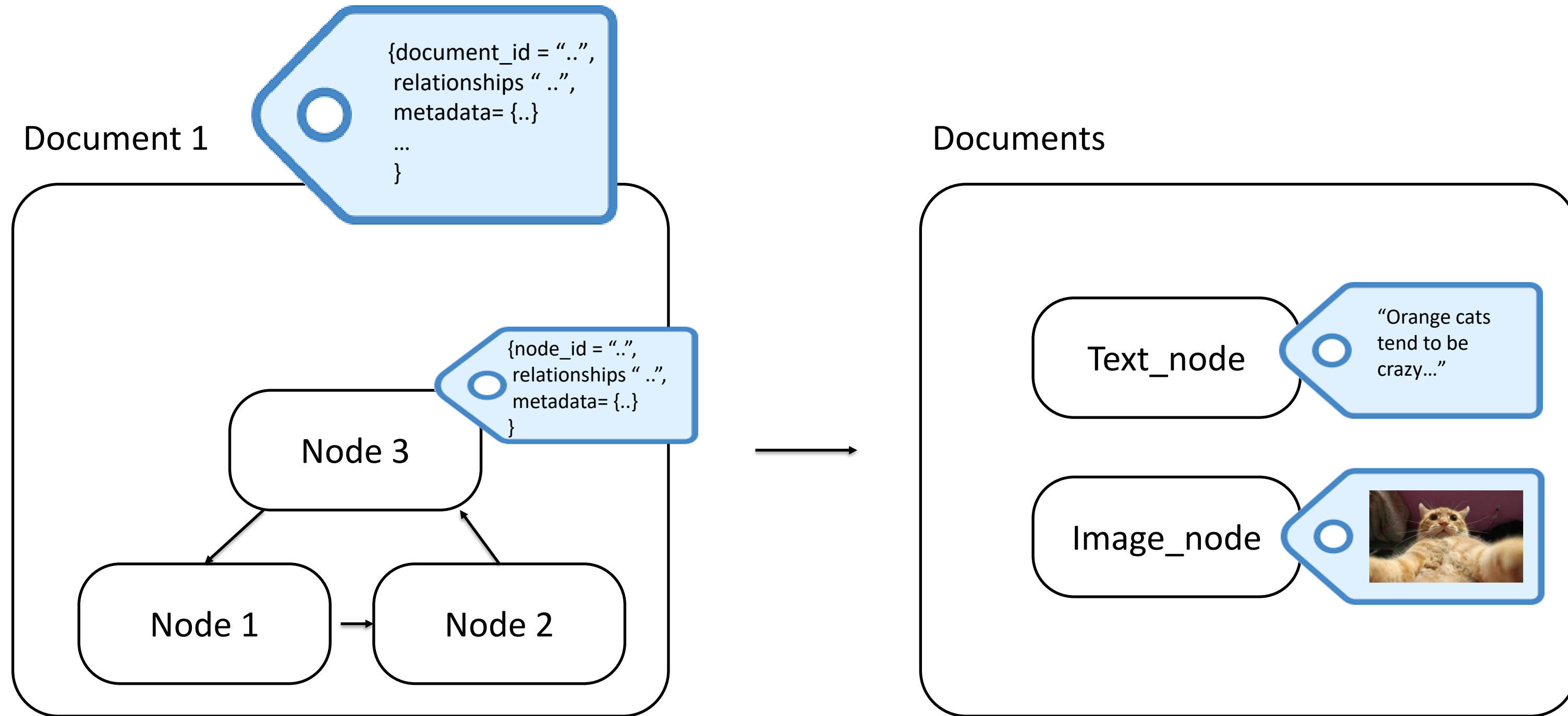
 **Data Connectors** to ingest data from various sources

 **Data Indexes** to structure your data in intermediate representations

 **Engines** to interact with your data in natural language



# Nodes and Documents are first citizens in Llama-index





VALENTINA ALTO

APRIL 23, 2024

# THANK YOU!



Let's Keep in touch!

