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# Data Querying

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# Learning Objectives

**By the end of this module, you will:**

- Know how to pull information from the database



# Querying Introduction

Input Prompt

What did the fox do  
with the dog?

Output Prompt

The fox jumps over  
the lazy dog.

Embedding  
Model

1010  
1010



Vector Database



The fox jumps over  
the lazy dog.

1010  
1010

[0.5, 0.3, ..., 0.2]

o o o

{„author“: „...“, ...}

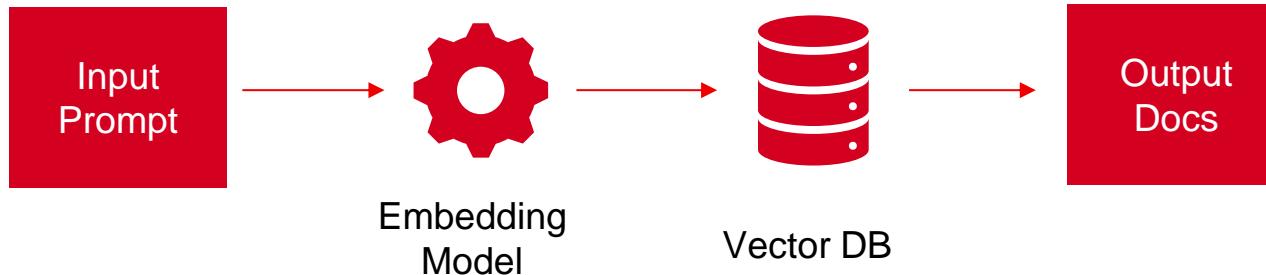


unique id1





# Text Querying

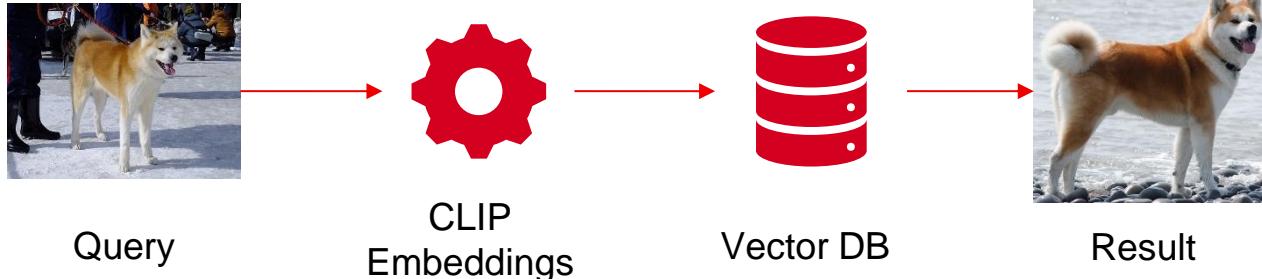


## Practical Implementation

```
collection.query(query_texts=[“This is my input text”])
```



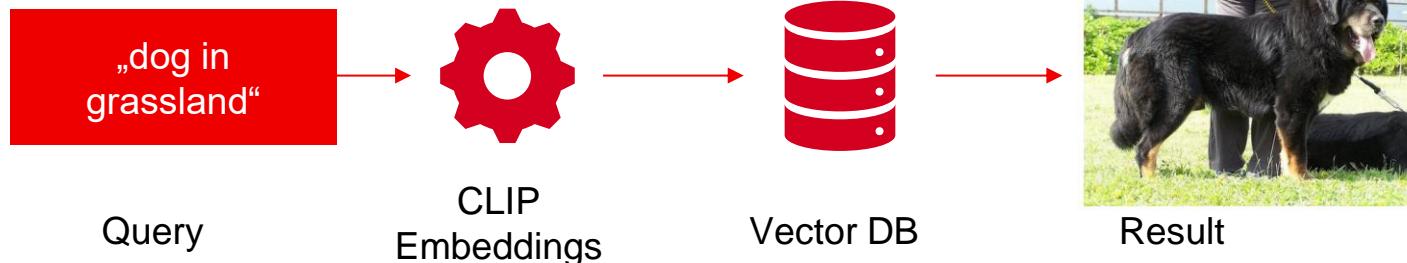
# Image Querying



```
query_list = ["./data/dogs/akita_1.jpg"]  
query_result = chroma_collection.query(  
    query_images = query_list,  
    n_results=3,  
    include=['documents',  
             'distances',  
             'metadatas', 'data',  
             'uris'],)
```

Result 1: ./data/dogs/akita\_3.jpg  
with distance: 0.17

# Image Querying



```
query_list = ["dog in grassland"]
query_result = chroma_collection.query(
    query_texts = query_list,
    n_results=3,
    include=[ 'documents',
              'distances',
              'metadatas', 'data',
              'uris'],)
```

Query: dog in grassland Result 0:  
..../data/dogs/mastiff\_1.jpg  
with distance: 0.85

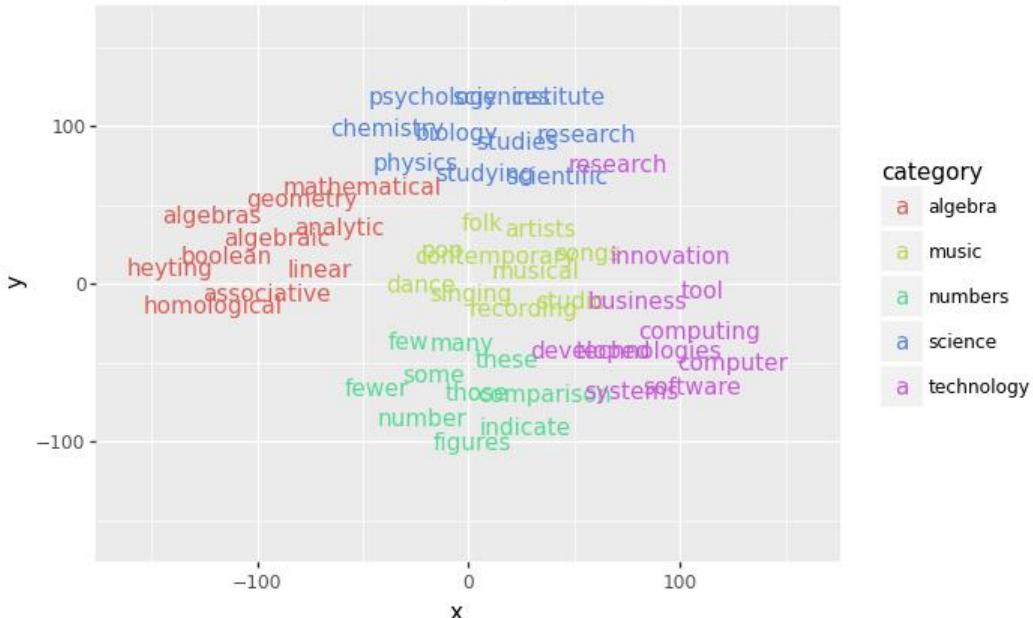


# Similarity

- Vector DB needs to analyze similarity of query-embedding compared to document embeddings.
- Approaches:
  - Cosine Similarity
  - Maximum Margin Relevance

# Similarity Search

GloVe Word Embeddings and Categories



$$dist = \sqrt{(x_1 - y_1)^2 + (x_n - y_n)^2}$$

For an embedding vector of 768 embeddings, there are 768 distance terms

Example: word embeddings reduced to 2 dimensions



# Similarity Search

Imagename

dog1

|     |      |     |     |     |     |
|-----|------|-----|-----|-----|-----|
| 0.3 | 0.02 | 0.8 | 0.6 | ... | 0.4 |
|-----|------|-----|-----|-----|-----|

dog2

|     |      |     |     |     |     |
|-----|------|-----|-----|-----|-----|
| 0.1 | 0.52 | 0.7 | 0.6 | ... | 0.4 |
|-----|------|-----|-----|-----|-----|

...

dogN

|     |      |     |     |     |     |
|-----|------|-----|-----|-----|-----|
| 0.3 | 0.62 | 0.9 | 0.2 | ... | 0.3 |
|-----|------|-----|-----|-----|-----|

Vector Database

Embedding

dogTest

|     |      |     |     |     |     |
|-----|------|-----|-----|-----|-----|
| 0.3 | 0.02 | 0.8 | 0.6 | ... | 0.4 |
|-----|------|-----|-----|-----|-----|



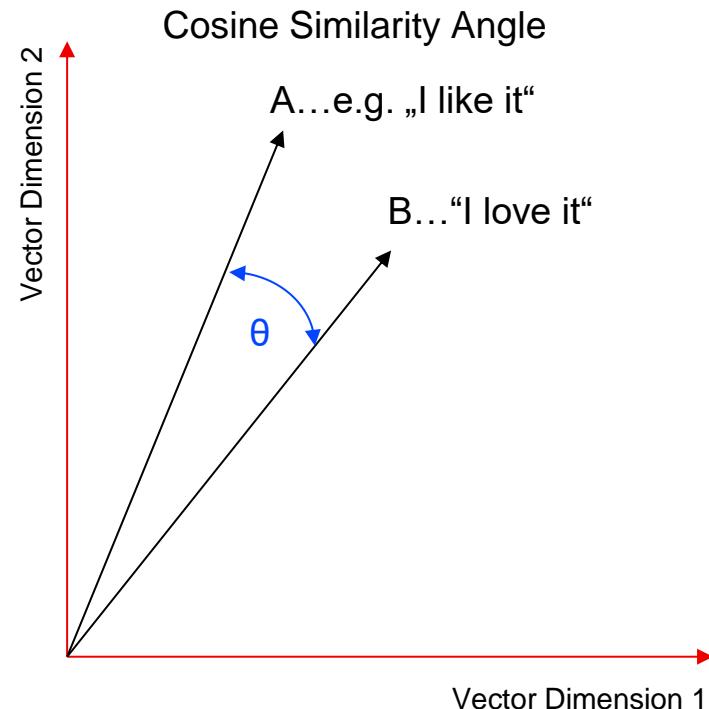
$$dist = \sqrt{\sum (x_i - y_i)^2}$$

For small data, go with `np.array()`.

For large dataset not feasible!

# Cosine Similarity

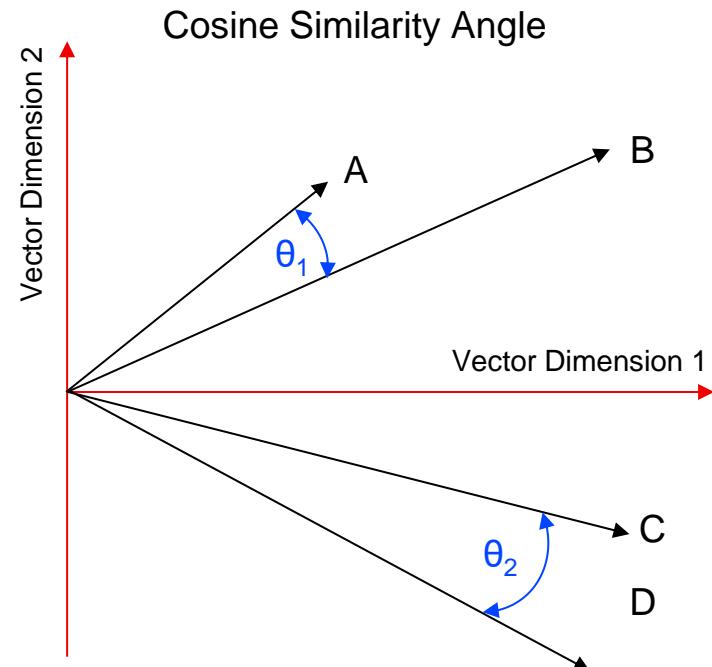
- Measures similarity between Embedding-Vectors based on angle  $\theta$ .
  - Vectors maximally dissimilar  
→ vectors perpendicular ( $\theta = 90^\circ$ )
  - Vectors completely similar  
→ vectors parallel ( $\theta = 0^\circ$ )





# Cosine Similarity

- Only the angle defines the similarity
- NOT the euclidean distance or magnitude of a vector
- Example
  - A: "The cat sleeps."
  - B: "The feline slumbers peacefully on the soft cushion."
  - C: "Trees grow leaves in spring."
  - D: "Fish swim in the ocean."



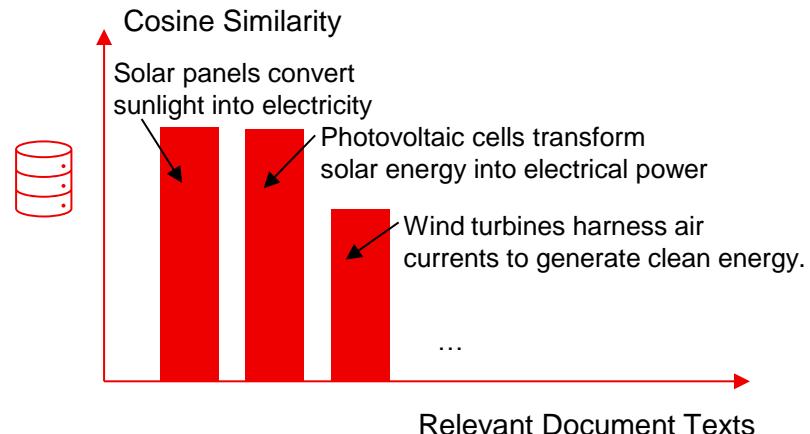
# Maximum Margin Relevance

Topic: Renewable Energies

- Approach: reduce redundancy while maintaining relevance and diversity
- Redundancy...similar vectors
- Relevance...how closely do query and documents match
- Avoid clustering effect



What are the main types of renewable energy sources and how do they work?



The background features a vibrant, warm color gradient transitioning from deep red on the left to bright yellow on the right. Overlaid on this gradient are several large, semi-transparent circular shapes in shades of red, orange, and yellow, creating a layered, sunburst-like effect.

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