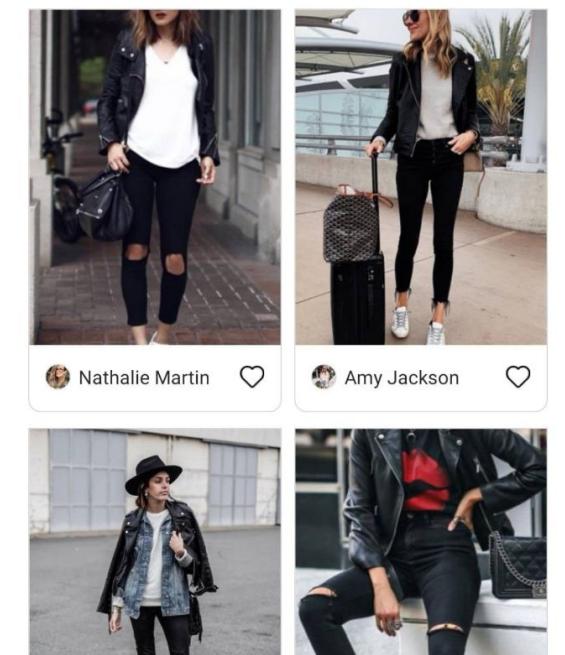
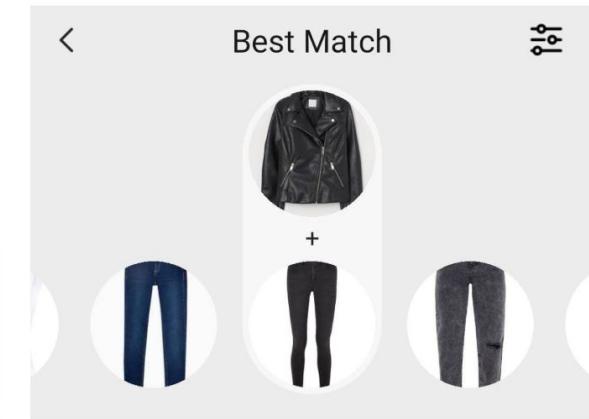
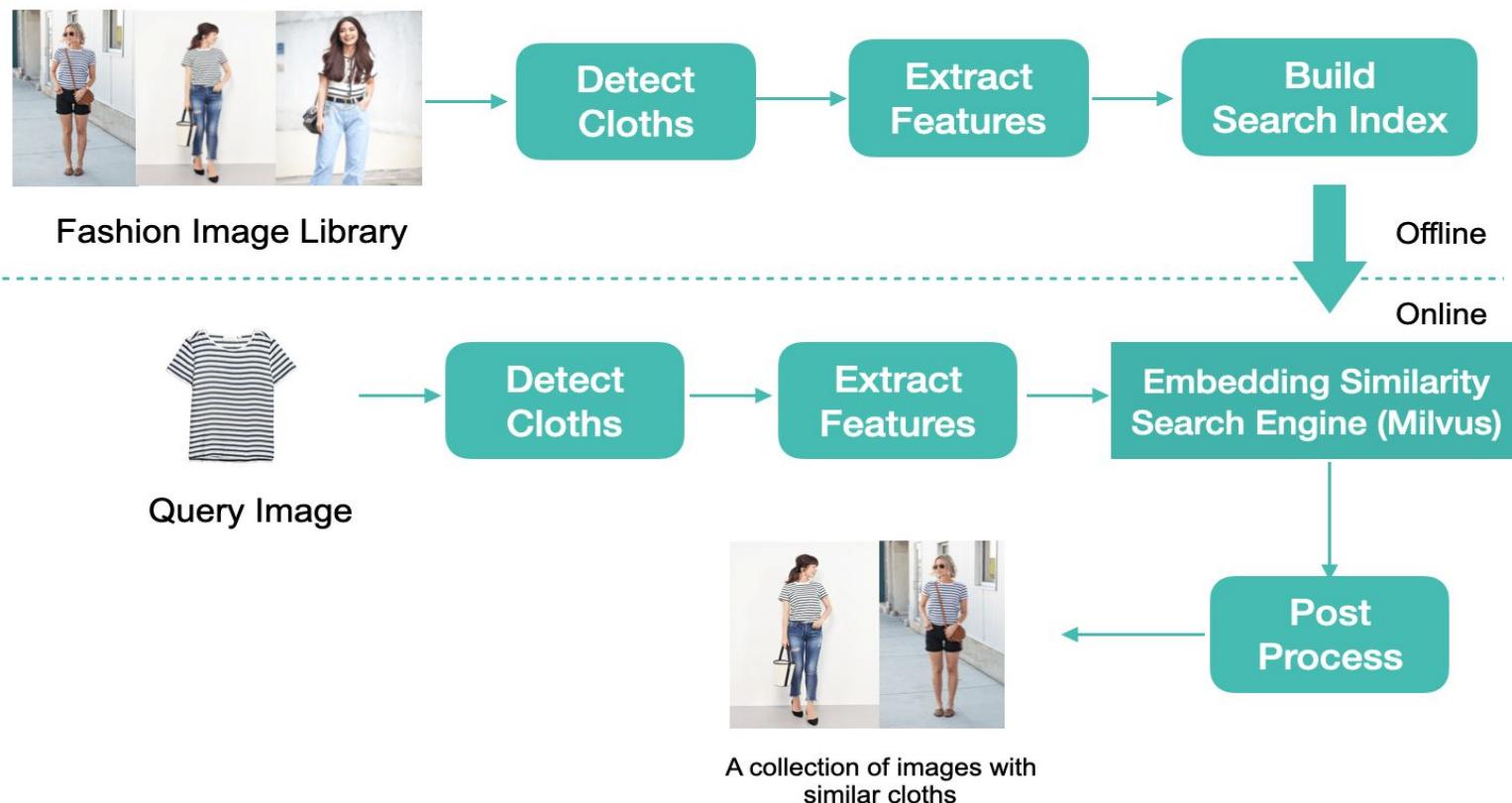


Project: Image Retrieval (TA Session)

Nguyễn Thọ Anh Khoa
Ph.D. Student

Objective

- ✓ Introduce image retrieval.
- ✓ Discuss similarity measurement techniques.
- ✓ Outline data preparation for image retrieval.
- ✓ Demonstrate a basic image retrieval system.
- ✓ Explore advanced retrieval with deep learning models.
- ✓ Implement image retrieval using vector databases.
- ✓ (Optional) Overview of web crawling for data acquisition.



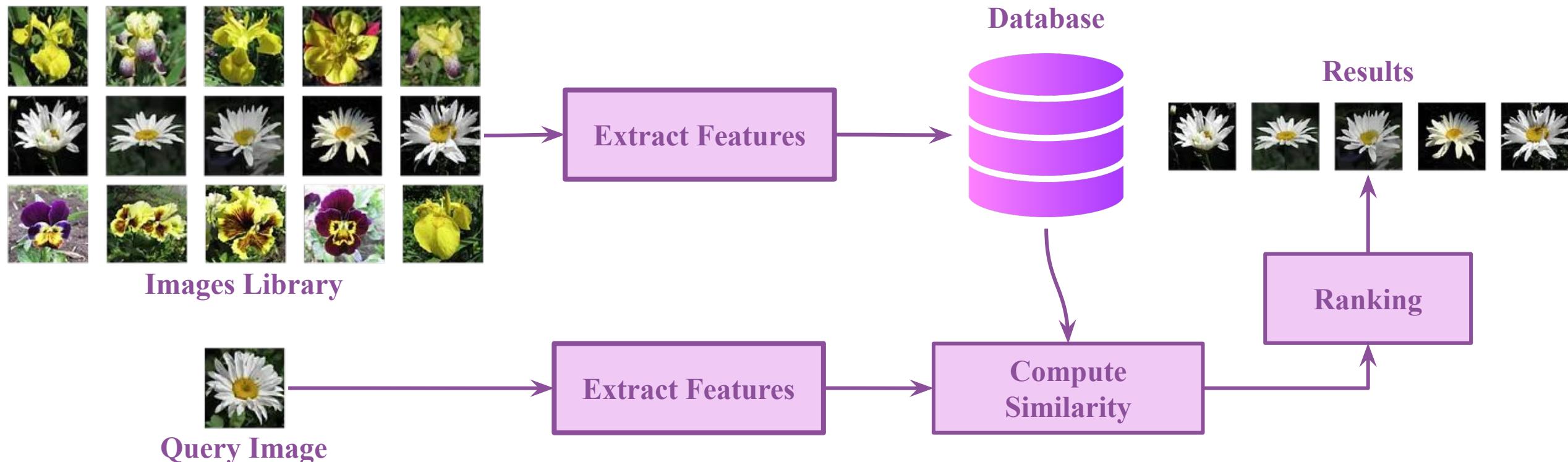
Outline

- **Introduction to Image Retrieval**
- **Similarity Measurement Techniques in Image Retrieval**
- **Data Preparation for Image Retrieval**
- **Basic Image Retrieval System**
- **Advanced Image Retrieval Using Pre-trained Deep Learning Model**
- **Implementing Image Retrieval with Vector Database**
- **Optional: Data Acquisition through Web Crawling**

Introduction to Image Retrieval

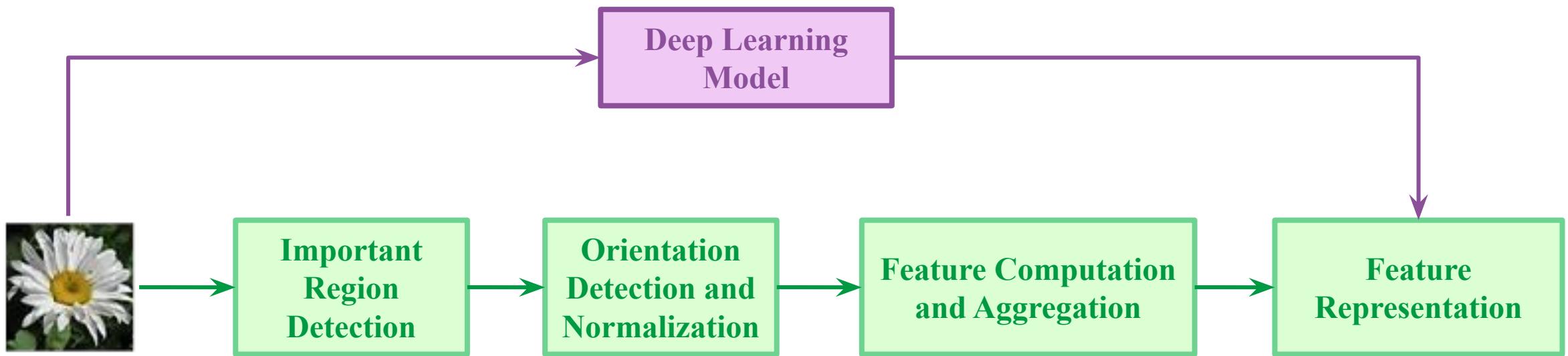
Introduction to Image Retrieval

Definition: The **content based image retrieval** aims to find the **similar images** from a **large scale dataset** against a **query image**. Generally, the similarity between the representative features of the query image and dataset images is used to **rank the images for retrieval**. In early days, various hand designed feature descriptors have been investigated based on the visual cues such as color, texture, shape, etc. that represent the images. However, the deep learning has emerged as a dominating alternative of hand-designed feature engineering from a decade. It learns the features automatically from the data

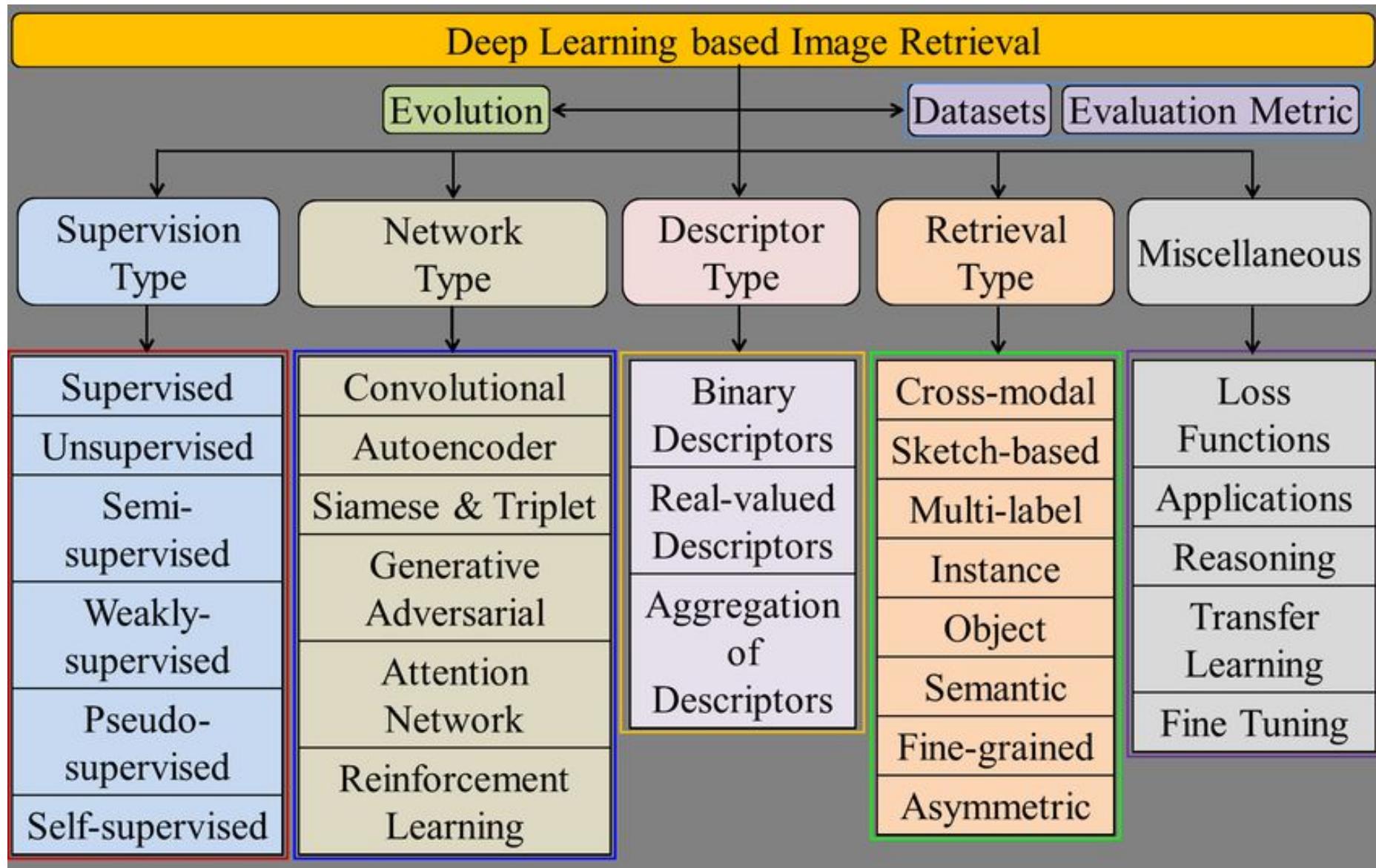


Introduction to Image Retrieval

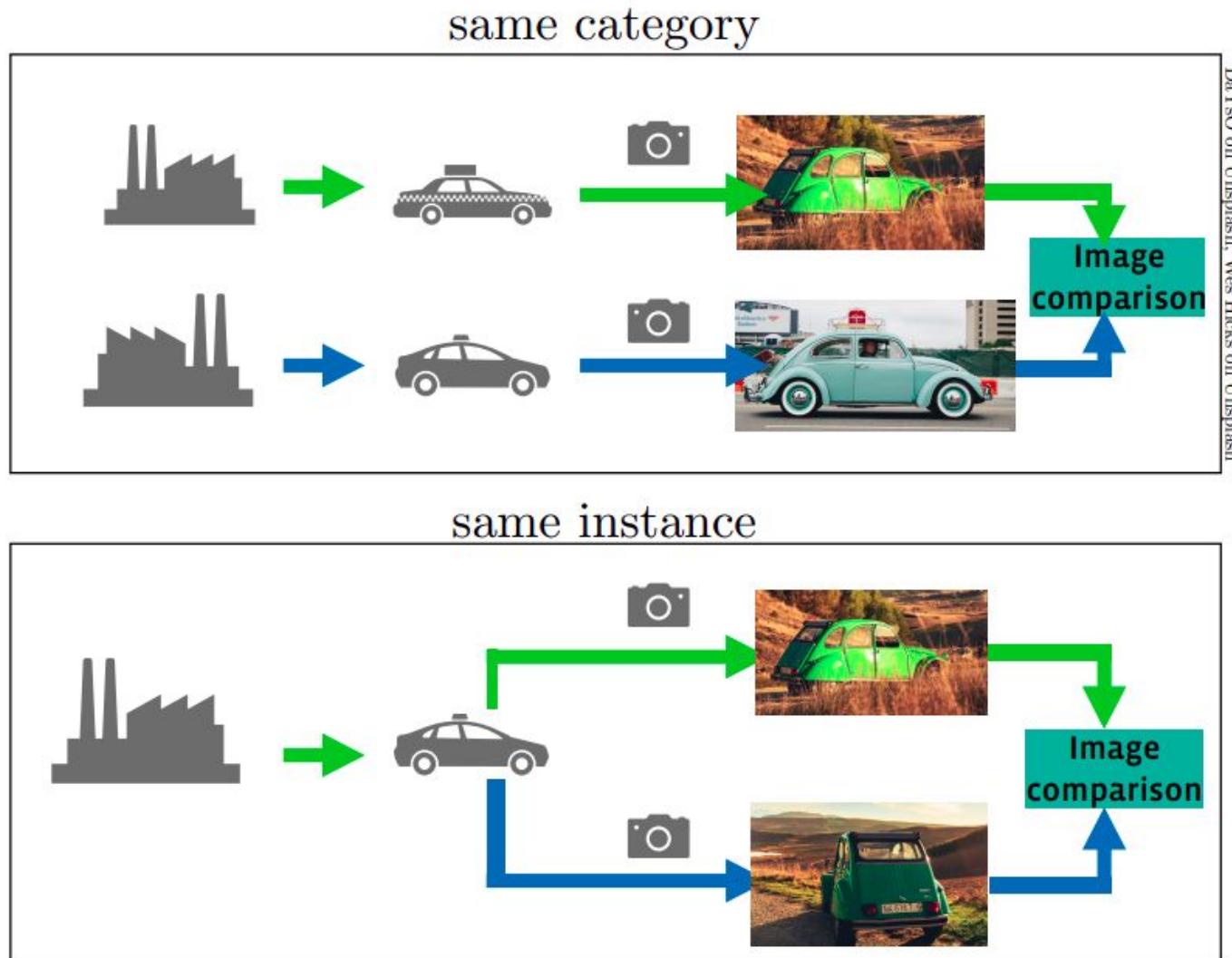
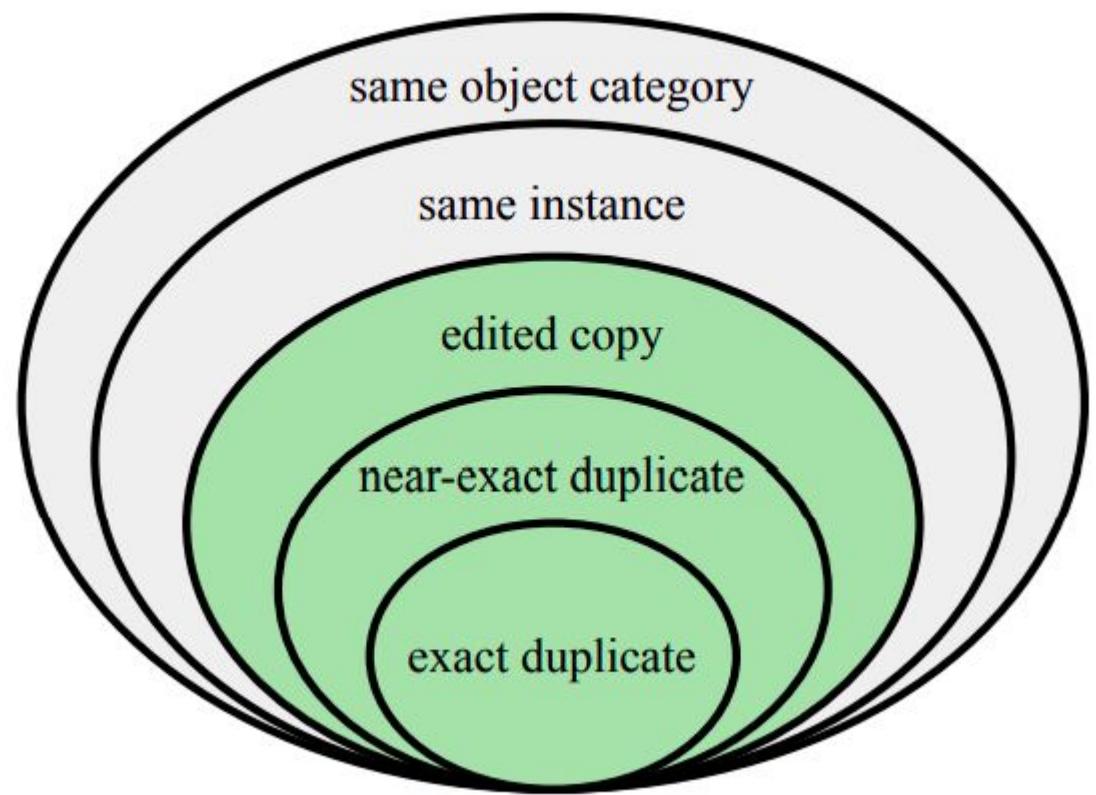
Definition: The **content based image retrieval** aims to find the **similar images** from a **large scale dataset** against a **query image**. Generally, the similarity between the representative features of the query image and dataset images is used to **rank the images for retrieval**. In early days, various hand designed feature descriptors have been investigated based on the visual cues such as color, texture, shape, etc. that represent the images. However, the deep learning has emerged as a dominating alternative of hand-designed feature engineering from a decade. It learns the features automatically from the data



Introduction to Image Retrieval



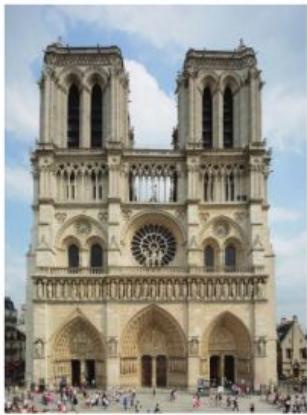
Introduction to Image Retrieval



Introduction to Image Retrieval



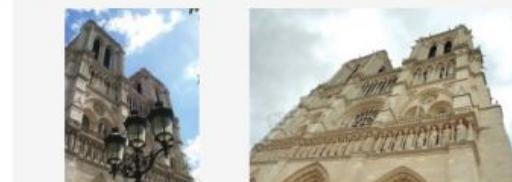
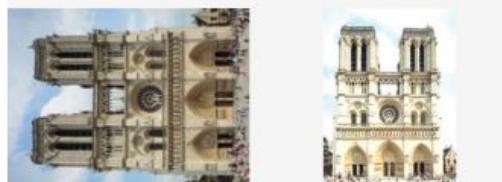
Duplicate
Retrieval



Instance
Retrieval



Category
Retrieval



Introduction to Image Retrieval

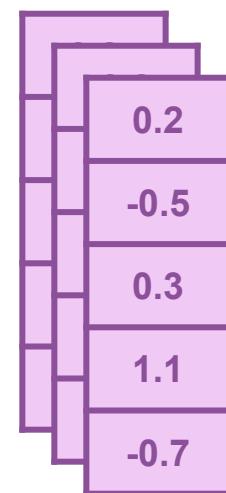
Project Pipeline



Images Library

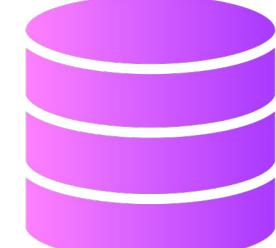
CLIP Model
(Pretrained Model)

Feature Vectors



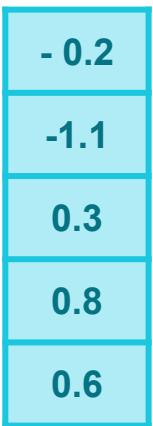
Indexing

(Chroma)
Vector
Database



CLIP Model
(Pretrained Model)

Feature Vector



Similarity
Computation

Ranking

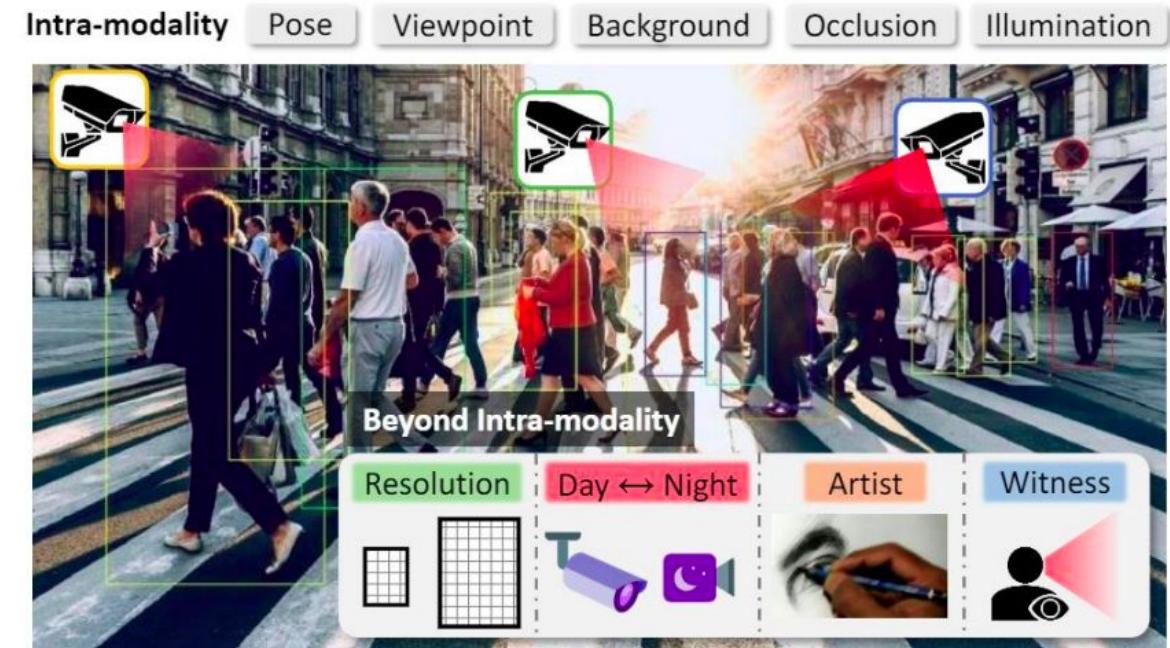
Results



Introduction to Image Retrieval

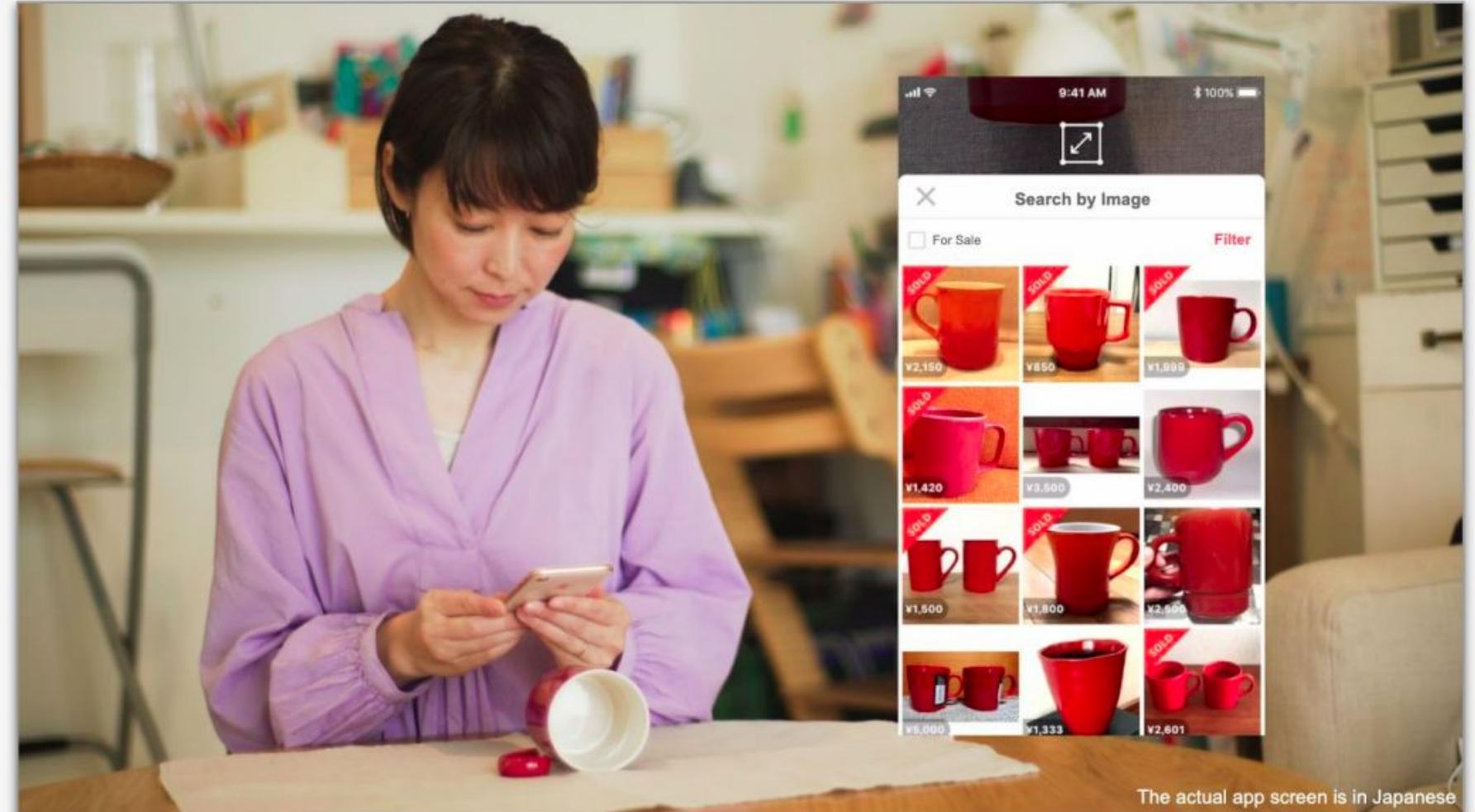
Practical and large-scale visual search system for real-world applications

- Discovering visually similar items in online marketplace apps
- Re-identification for pedestrians in a security scenario.



Introduction to Image Retrieval

- Amazon
- eBay
- Asos
- Alibaba
- Taobao
- AliExpress
- Mercari
- etc...



The actual app screen is in Japanese

The visual search feature on the Mercari Japan app [\[Promotional Video\]](#)

Introduction to Image Retrieval

How do you query when you look for clothes like this?



- “Plaid” and “Shirt”?
- “Plaid” and “Blouse”?
- “Checks” and “Blouse”?
- “Checks” and “Blouse” and “Frill”?
- “Gingham Plaid” and “Blouse” and “Frill”?
- “Gingham Plaid” and “Blouse” and “Frill” and “Collar”?
- ...

Introduction to Image Retrieval

Visual Search

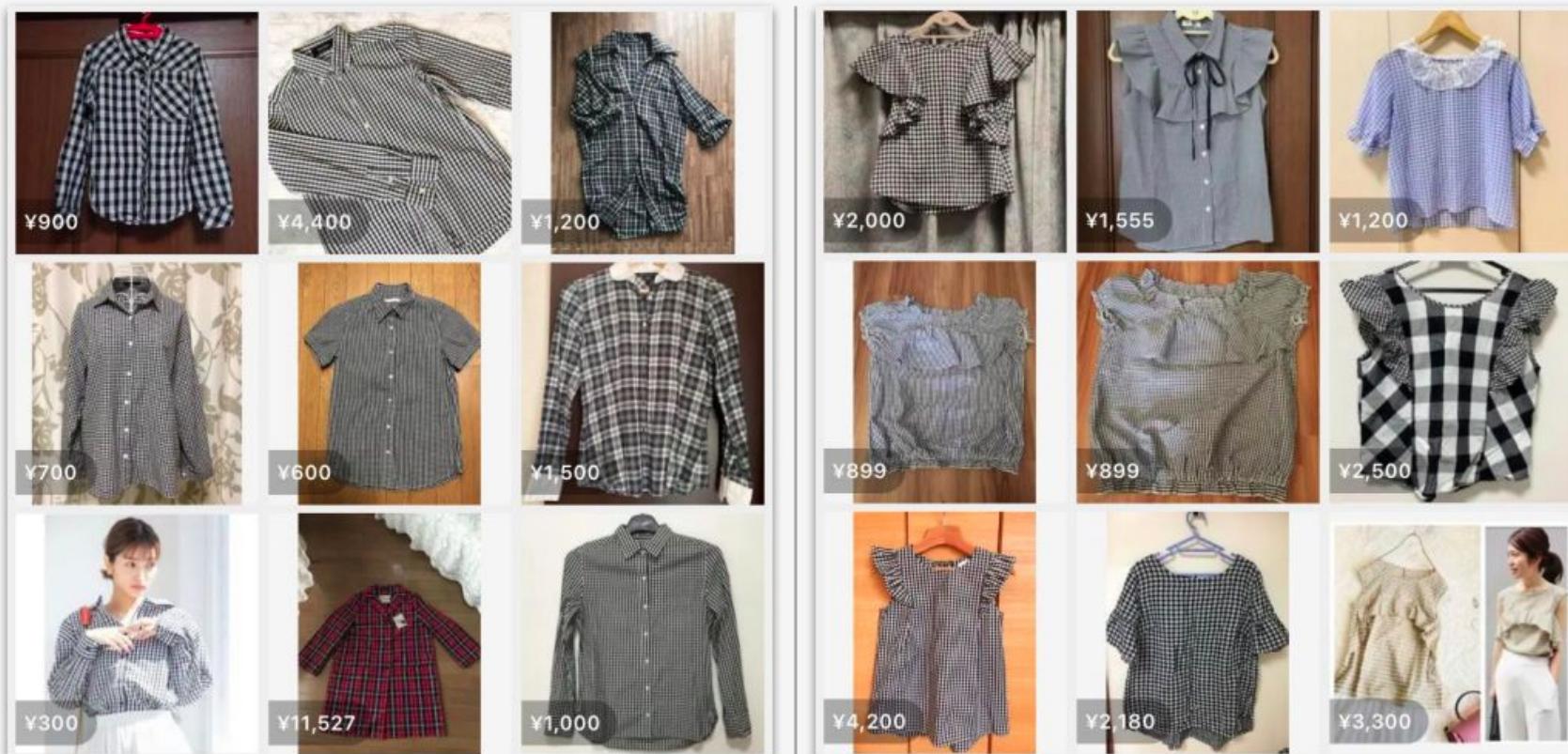


Query:



Query: “black white plaid shirt”

Text-based Search



Query: “Gingham Plaid Frill Blouse”

Introduction to Image Retrieval

Visual Search

iPhone XS

iPhone 6s / 7

iPhone X

Query:

(iPhone XS Max 256GB)

Text-based Search

iPhone XS Max 256GB

Query: "iphone xs max 256gb"

Text-based search is better when:

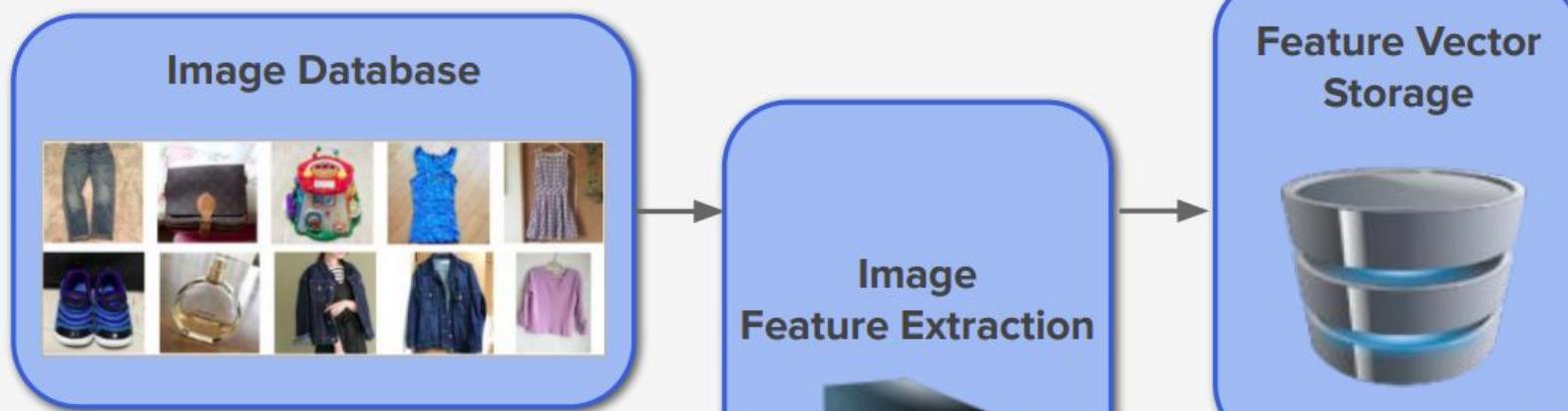
- sellers and buyers describe products in the same way**
- visual information is not enough to explain products**

M (c) 2020 Mercari, Inc.

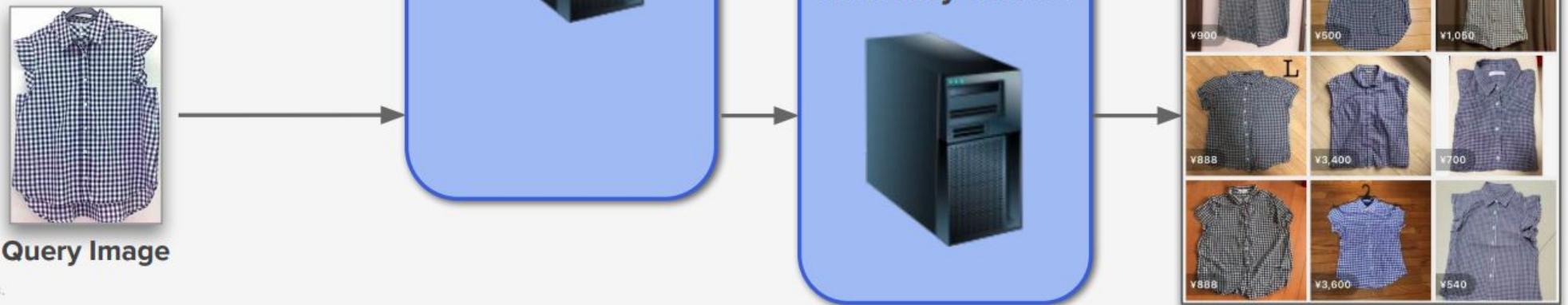
11

(*) The visual search is available only on the Mercari Japan iOS app as of now

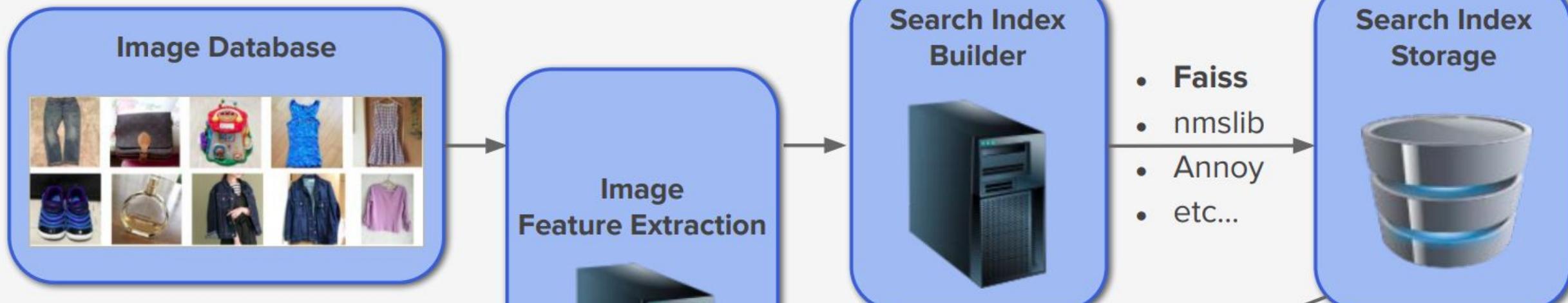
Indexing



Search



Indexing



Search

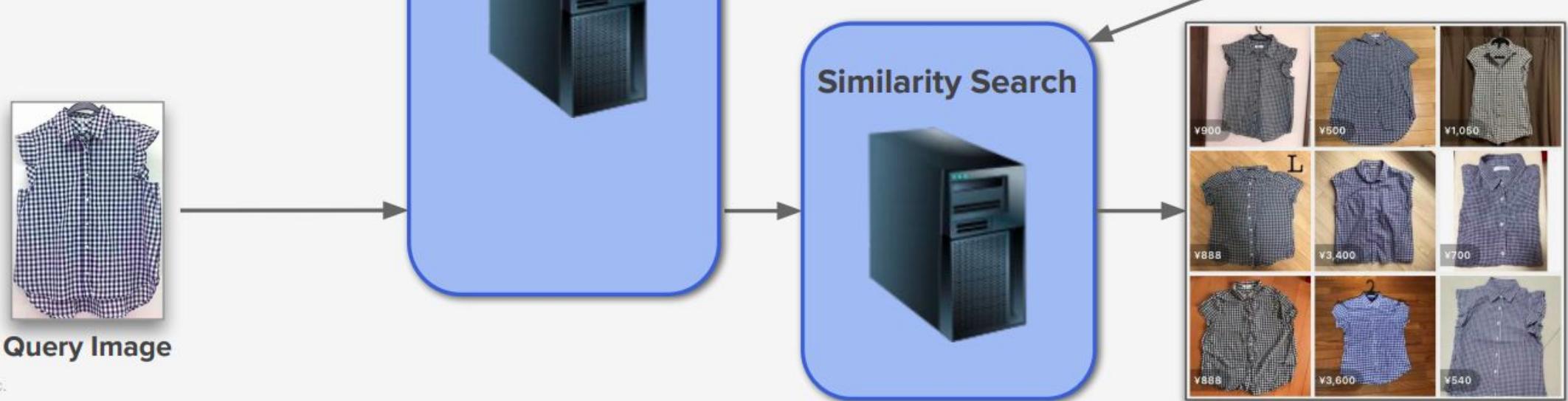


Image labeling

Image labels: ?

- Amanita mu... + -
- Armillaria m... + -
- Boletus edulis + -
- Cantharellus... + -
- Macrolepiot... + -

Labels add

The label encircled in white is the default label.

Clear similarity history

2022 Aug 17 13:28

2022 Aug 17 13:01

Query image



Download results

Download top scoring images by similarity: [Download](#)

Results in JSON format: [Download](#)

Results in CSV format: [Download](#)

Top scoring images by similarity

Image ID	Score	Label
c6eb9f9a8feb57e2d924...	80%	Amanita mu...
4baea37f6a0f02a77900...	79%	Amanita mu...
73dd15275910f0617801cb...	76%	Amanita mu...
694604c7f7088182b3731...	76%	Amanita mu...

Score: 80% 

Score: 79% 

Score: 76% 

Score: 76% 

Introduction to Image Retrieval

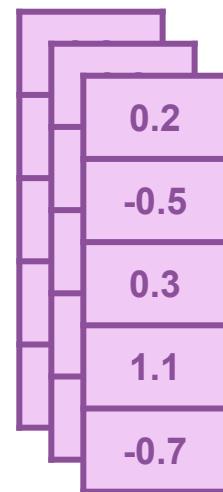
Summary



Images Library

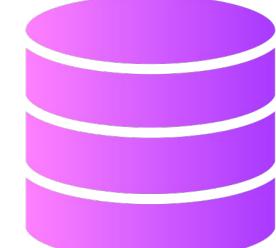
CLIP Model
(Pretrained Model)

Feature Vectors



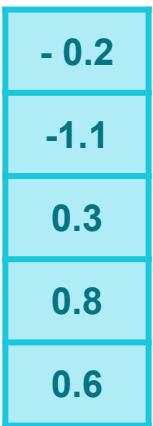
Indexing

(Chroma)
Vector
Database



CLIP Model
(Pretrained Model)

Feature Vector



Similarity
Computation



Ranking

Results

Introduction to Image Retrieval

Content based image retrieval được định nghĩa là gì?

- A. Tạo hình ảnh mới từ các hình ảnh hiện có.
- B. Tìm kiếm và lấy hình ảnh từ cơ sở dữ liệu dựa trên nội dung của chúng.
- C. Chỉnh sửa màu sắc và độ sáng của hình ảnh.
- D. Chuyển đổi hình ảnh sang các định dạng khác.

Similarity Measurement Techniques in Image Retrieval

Distance Metrics and Similarity

Distance Metrics:

- **Definition:** Mathematical measures used to calculate the distance (or similarity) between two elements in a vector space.
- **Purpose:** Evaluate how far apart or how similar two elements are.

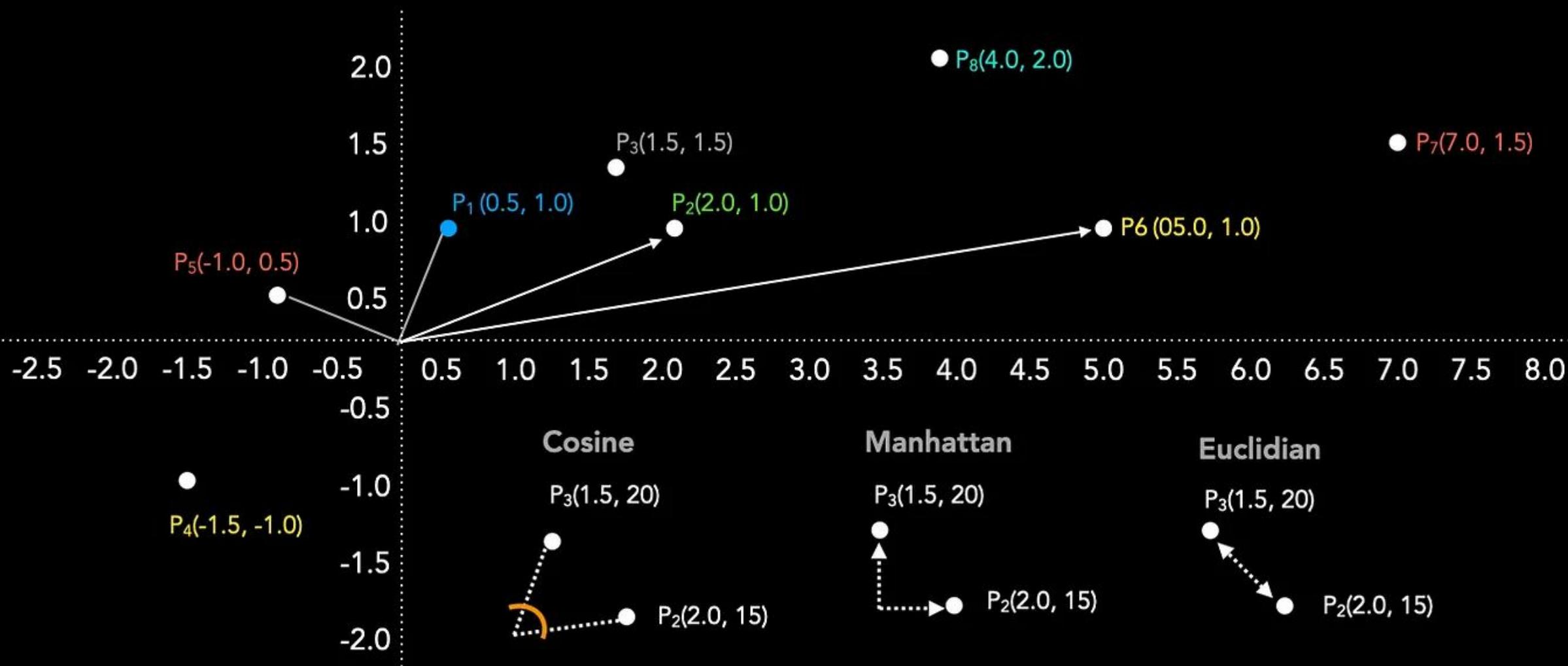
Context of Embeddings:

- **Definition:** Embeddings are vector representations of data points.
- **Role of Distance Metrics:** In this context, distance metrics are used to assess the similarity between embeddings.

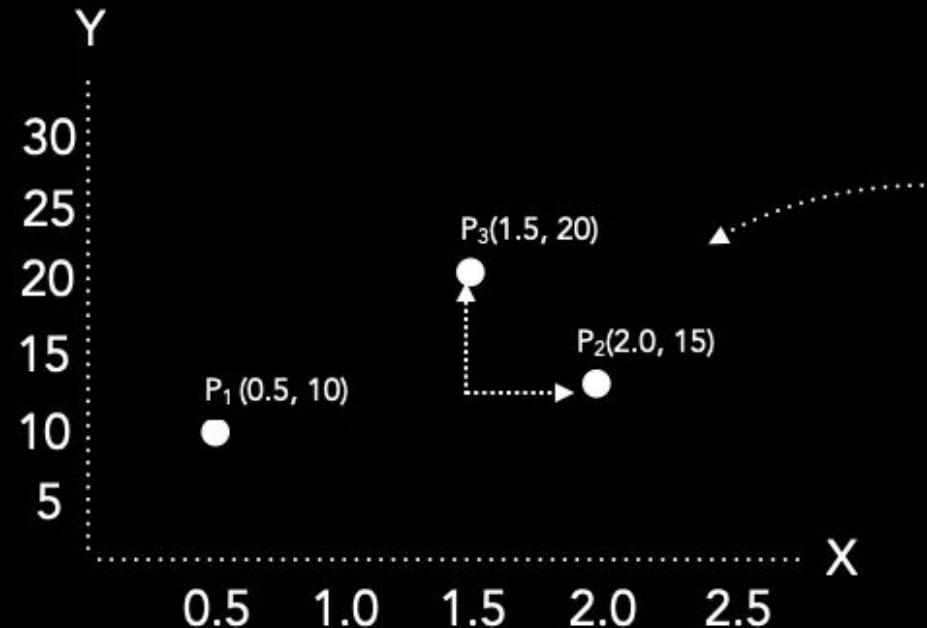
Similarity Query Search:

- **Function:** Retrieves embeddings that are similar to a given input.
- **Based On:** Uses distance metrics to determine which embeddings are close to the input in the vector space.

Distance Metrics and Similarity



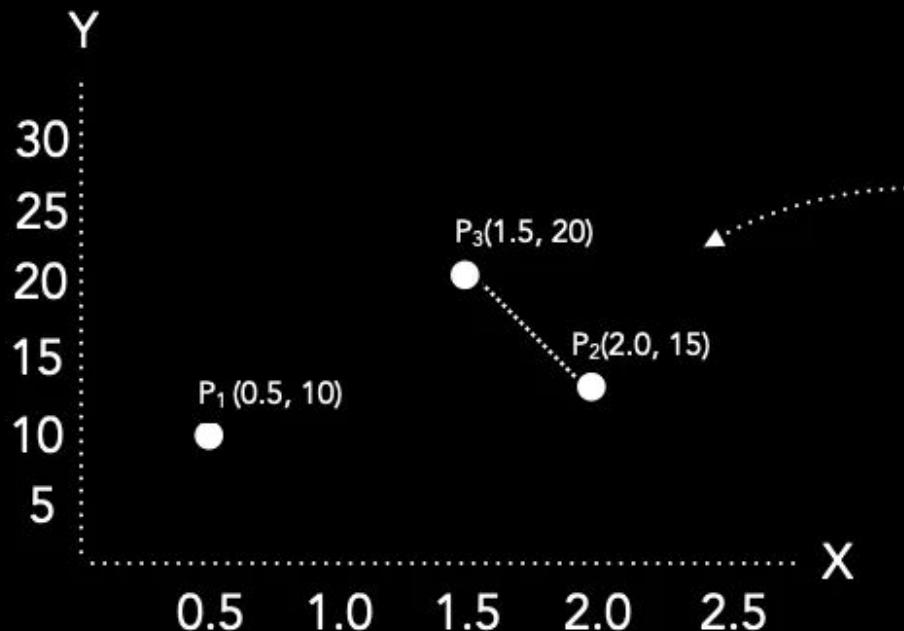
Manhattan Distance L1



Manhattan distance L1 between P_3 and P_2

$$\begin{aligned}\|P_3 - P_2\| &= \sum |P_{3[i]} - P_{2[i]}| \\ &= |1.5 - 2.0| + |20 - 15| = 5.5\end{aligned}$$

Euclidean Distance L2

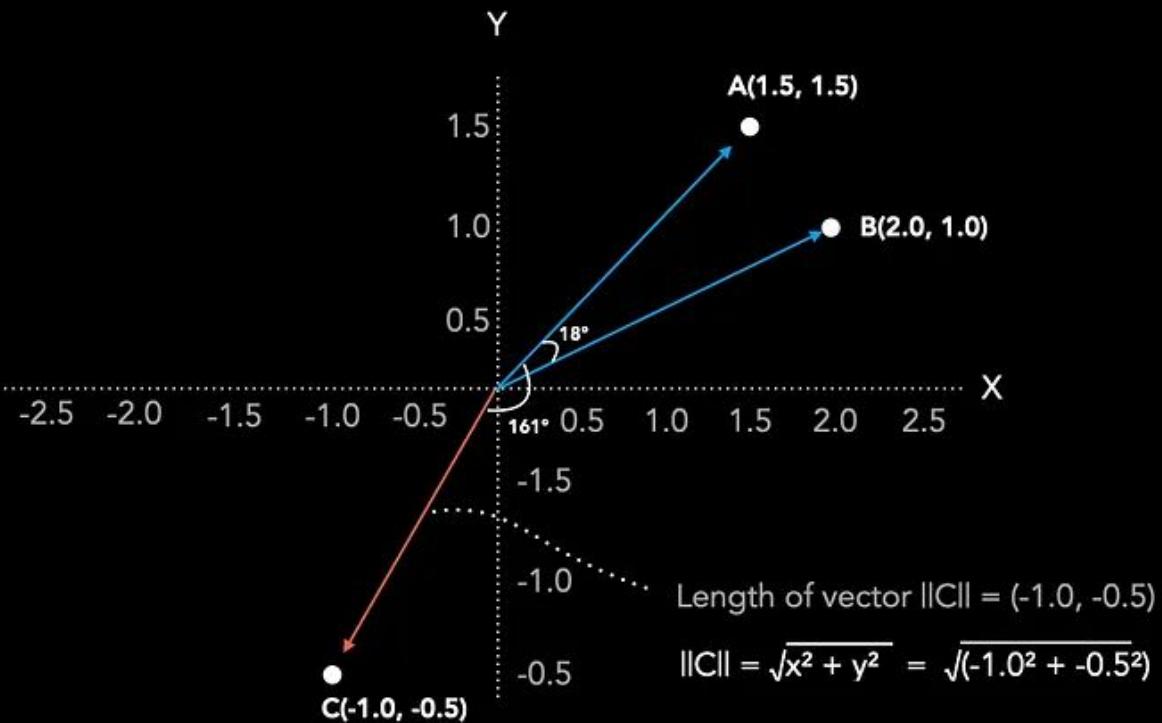


Euclidian distance L2 between P₃ and P₂

$$\begin{aligned}\| \mathbf{P}_3 - \mathbf{P}_2 \| &= \sqrt{\sum |P_{3[i]} - P_{2[i]}|^2} \\ &= \sqrt{(1.5 - 2.0)^2 + (20 - 15)^2} = 5.2\end{aligned}$$

Similarity Measurement Techniques in Image Retrieval

Cosine Similarity



Cosine similarity between A vs B and A vs C:

$$\text{Cos}(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \cdot \|\mathbf{B}\|} = \frac{\mathbf{A} \cdot \mathbf{B}}{\sqrt{\sum_{i=1}^n A_i^2} \cdot \sqrt{\sum_{j=1}^n B_j^2}}$$

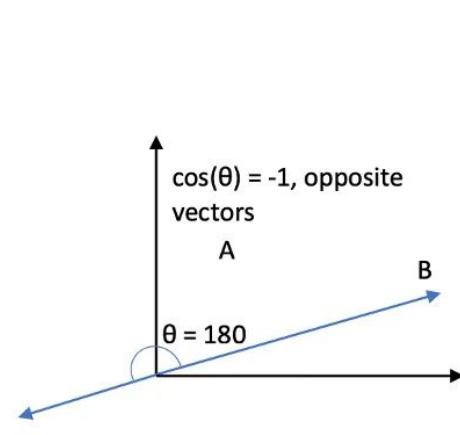
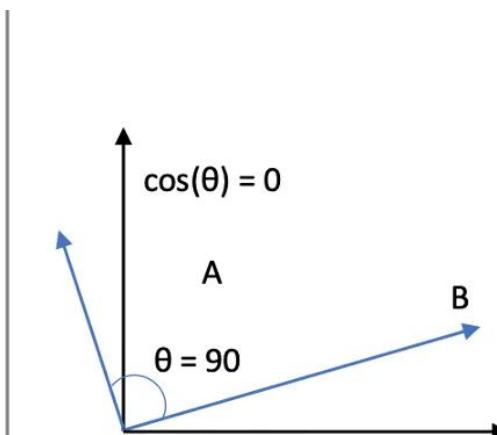
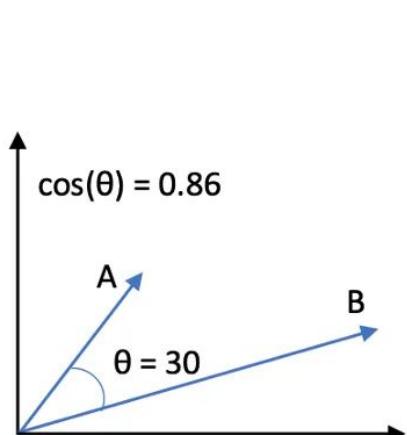
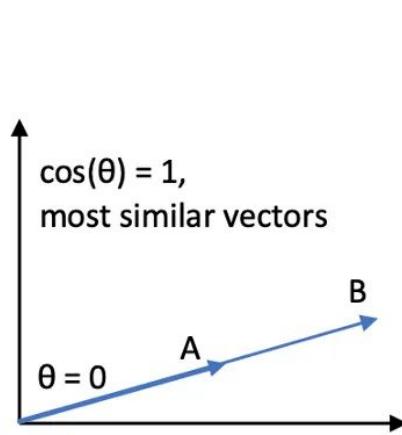
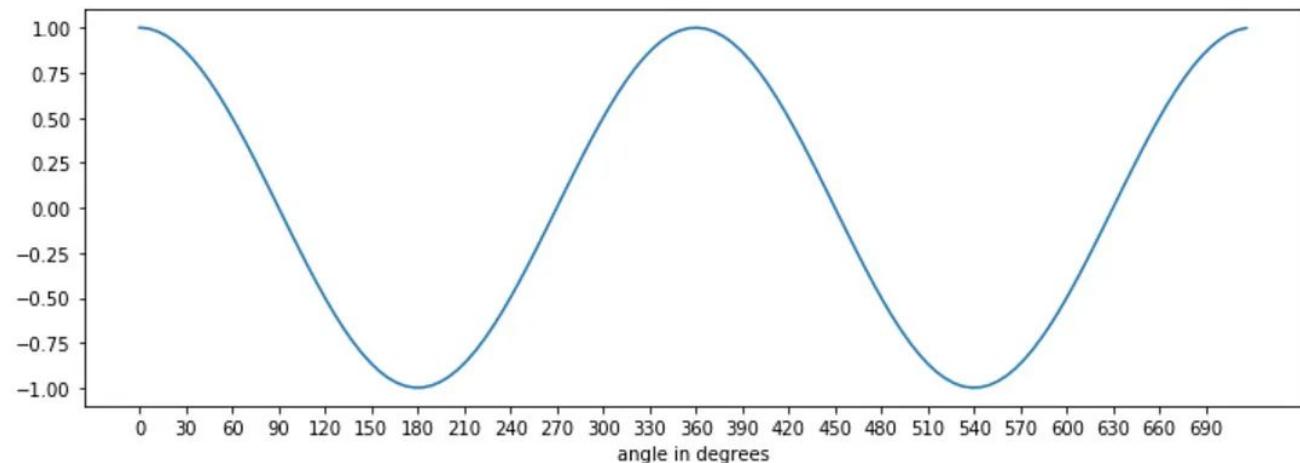
- Dot Product
- Length of each Vector

$$\begin{aligned} \text{A } (1.5, 1.5) &= \frac{1.5 \cdot 2.0 + 1.5 \cdot 1.0}{\sqrt{(1.5^2 + 1.5^2)} \cdot \sqrt{2.0^2 + 1.0^2}} = \cos(\theta) = 0.948 \\ \text{B } (2.0, 1.0) & \quad \quad \quad \text{Angle } \theta = 18^\circ \end{aligned}$$

$$\begin{aligned} \text{A } (1.5, 1.5) &= \frac{1.5 \cdot -1.0 + 1.5 \cdot -0.5}{\sqrt{(1.5^2 + 1.5^2)} \cdot \sqrt{-1.0^2 + -0.5^2}} = \cos(\theta) = -0.9487 \\ \text{C } (-1.0, -0.5) & \quad \quad \quad \text{Angle } \theta = 161^\circ \end{aligned}$$

Cosine Similarity

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

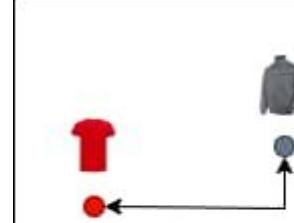


Distance Metrics and Similarity



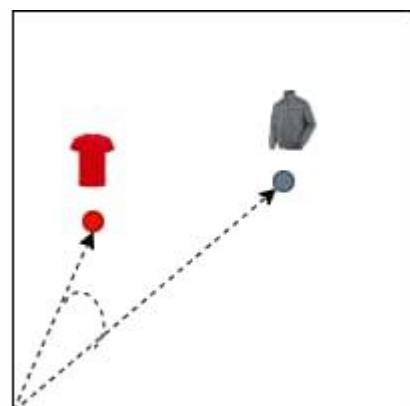
Euclidean Distance:

- **Definition:** Measures the straight-line distance between two points in Euclidean space.
- **Use Case:** Used to determine how far apart two points are in a straight line, considering both the magnitude and direction of the vectors.



Manhattan Distance (L1 Norm):

- **Definition:** Sums the absolute differences of the coordinates of two points.
- **Use Case:** Measures distance by moving along grid lines, often used in contexts where movements are restricted to orthogonal directions.



Cosine Similarity:

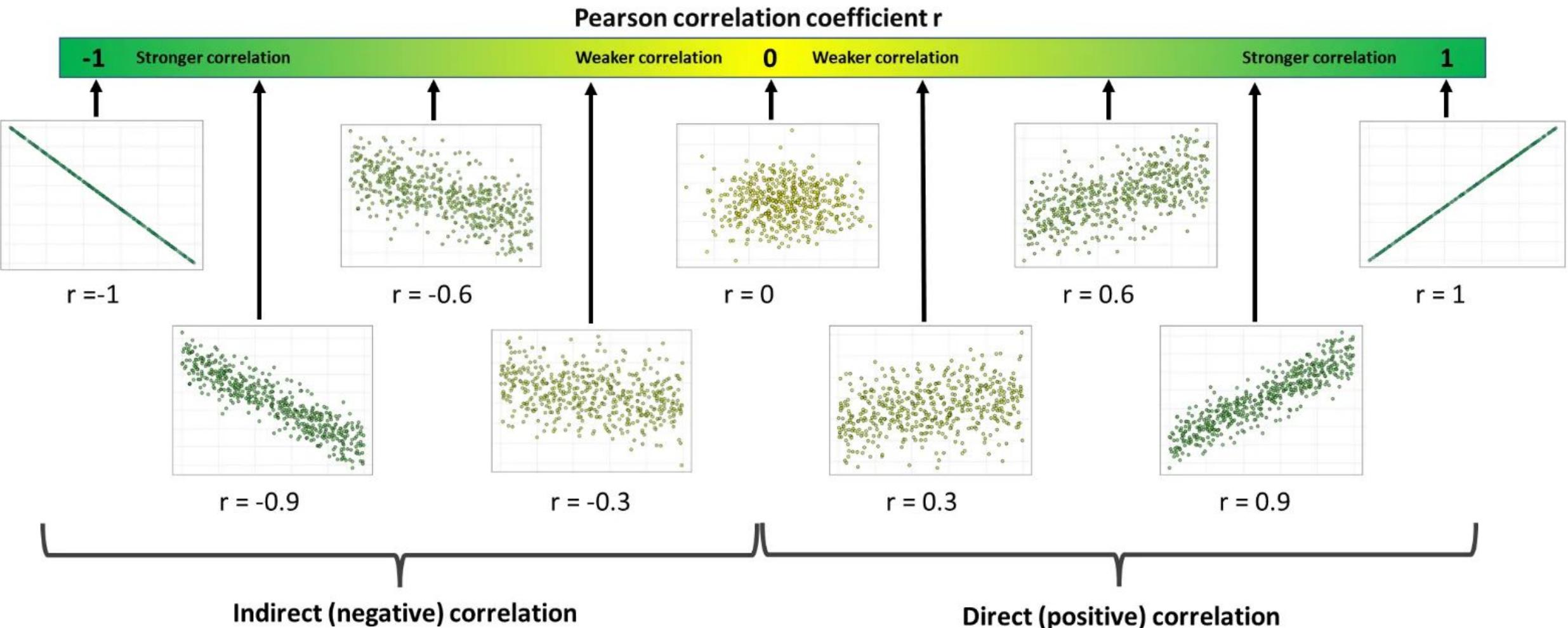
- **Definition:** Measures the cosine of the angle between two vector embeddings.
- **Use Case:** Commonly used in text analysis and other domains where the direction of the vector is more important than its magnitude

Feature	L1 Distance (Manhattan)	L2 Distance (Euclidean)	Cosine Similarity
Definition	Sum of the absolute differences between the coordinates of the vectors.	Square root of the sum of the squared differences between the coordinates of the vectors.	Measures the cosine of the angle between two non-zero vectors.
Range	$[0, \infty)$	$[0, \infty)$	$[-1, 1]$
Usage in Vector Search	Useful when differences in each dimension are important and dimensions are not correlated.	Commonly used due to its straightforward interpretation as the straight-line distance.	Preferred when the magnitude of vectors is less important than their direction.
Sensitivity to Scale	Sensitive; can be affected by scale of dimensions.	Sensitive; can be affected by scale of dimensions.	Not sensitive; invariant to vector scaling.
Impact of Outliers	More robust to outliers compared to L2.	Less robust to outliers due to squaring the differences, making outliers more influential.	Not directly affected by outliers in magnitude, but can be affected by the direction of vectors.
Common Applications	Image processing, text analysis where dimensional independence is key.	Clustering, nearest neighbor searches where Euclidean space properties are desired.	Text similarity, information retrieval, and any application where the direction of vectors is more important than their magnitude.

Absolute value	Interpretation
0.8 to 1	Very strong relationship
0.6 to 0.8	Strong relationship
0.4 to 0.6	Moderate relationship
0.2 to 0.4	Weak relationship
0 to 0.2	Weak or correlation

$$\rho_{X,Y} = \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y} = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}}$$

Similarity Measurement Techniques in Image Retrieval



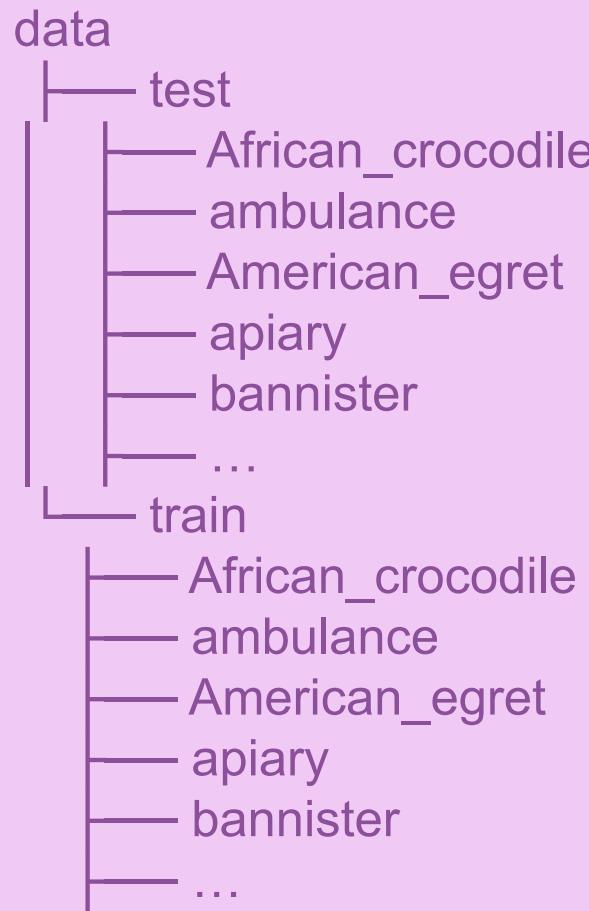
Đối với hai vector có chiều dài bằng nhau, phương pháp nào sau đây được sử dụng để đo sự tương đồng hướng giữa chúng?

- A. L1 distance
- B. L2 distance
- C. Cosine similarity
- D. Euclidean distance

Data Preparation for Image Retrieval

Data Preparation for Image Retrieval

Dataset

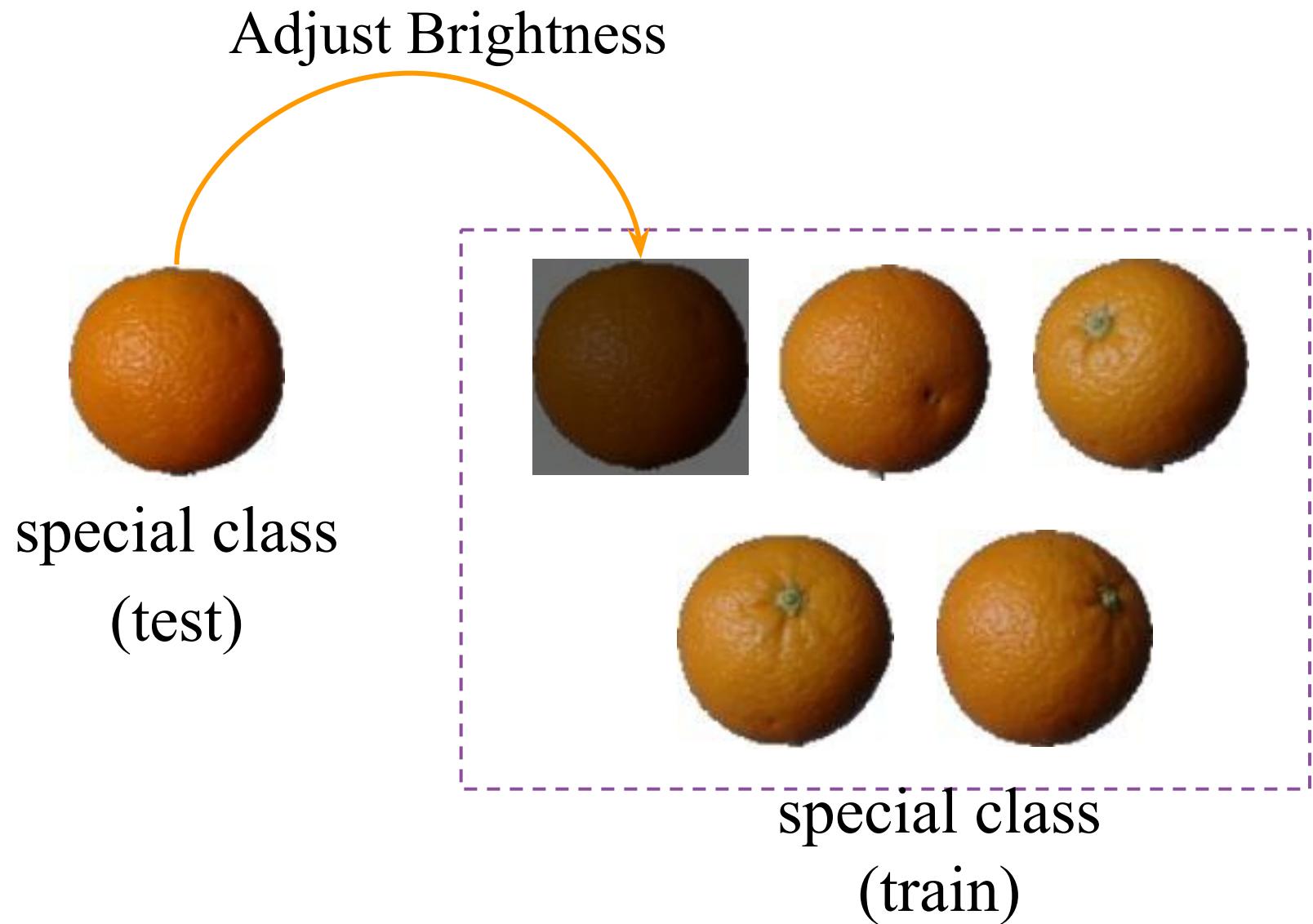
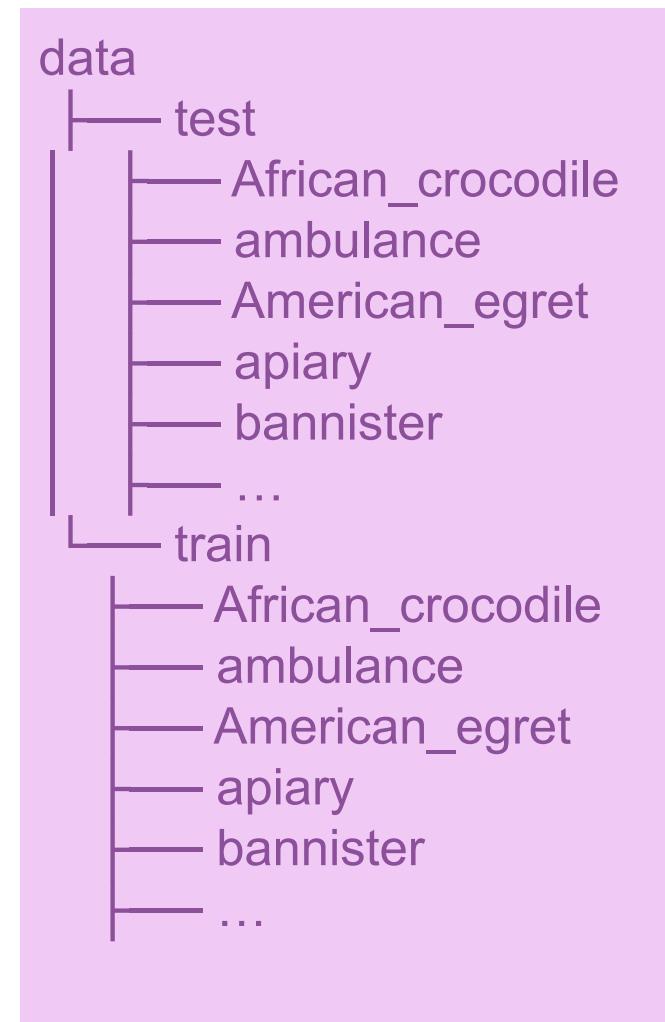


Subset of ImageNet1K

- Categories: 59 Classes + 1 special class
- Train: 9 samples/class (5 samples for special class)
- Test: 1 sample/class (1 samples for special class)

Data Preparation for Image Retrieval

Dataset



Data Preparation for Image Retrieval

Import Library/Modules

```
1 import os
2 import numpy as np
3 from PIL import Image
4 import matplotlib.pyplot as plt
```

```
['African_crocodile', 'American_egret', 'Doberman', 'Lakeland_terrier',
'Orange_easy', 'Rhodesian_ridgeback', 'ambulance', 'apiary', 'bannister',
'barn_spider', 'basketball', 'black_widow', 'brain_coral', 'bullet_train',
'can_opener', 'capuchin', 'car_mirror', 'carousel', 'castle', 'china_cabinet',
'cliff_dwelling', 'comic_book', 'conch', 'cornet', 'dugong',
'electric_locomotive', 'flamingo', 'flatworm', 'goldfish', 'grocery_store',
'guillotine', 'half_track', 'hen-of-the-woods', 'horizontal_bar', 'killer_whale',
'kit_fox', 'knee_pad', 'lion', 'loudspeaker', 'lynx', 'magpie', 'meat_loaf',
'mixing_bowl', 'parachute', 'pizza', 'ram', 'red-backed_sandpiper',
'ruffed_grouse', 'safety_pin', 'scabbard', 'screen', 'steam_locomotive',
'steel_arch_bridge', 'theater_curtain', 'traffic_light', 'triceratops',
'vine_snake', 'warplane', 'white_stork', 'yaw!']
```

```
1 ROOT = 'data'
2 CLASS_NAME = sorted(list(os.listdir(f'{ROOT}/train')))
```

```
1 def read_image_from_path(path, size):
2     im = Image.open(path).convert('RGB').resize(size)
3     return np.array(im)
```



All images must have same size

Data Preparation for Image Retrieval

```
5 def folder_to_images(folder, size):  
6     list_dir = [folder + '/' + name for name in os.listdir(folder)]  
7     images_np = np.zeros(shape=(len(list_dir), *size, 3))  
8     images_path = []  
9     for i, path in enumerate(list_dir):  
10         images_np[i] = read_image_from_path(path, size)  
11         images_path.append(path)  
12     images_path = np.array(images_path)  
13     return images_np, images_path
```

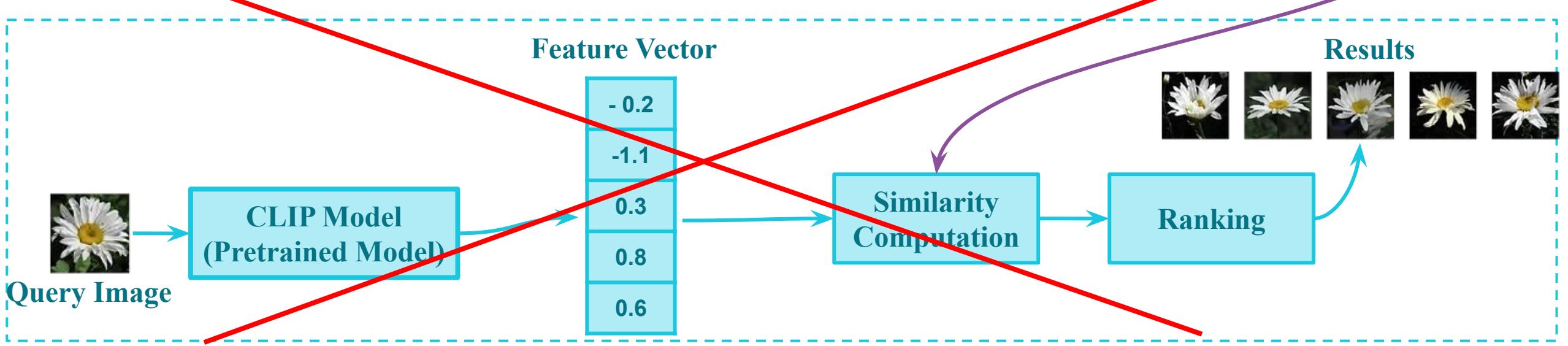
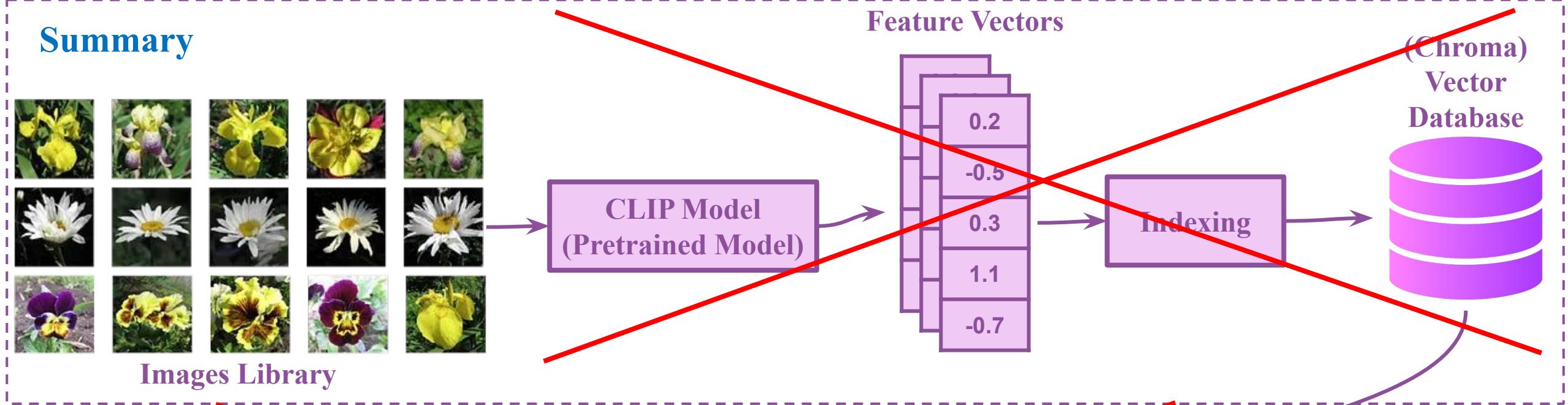
"List all file paths for images belonging to a specific class

Load all images belonging to a specific class and return them along with their corresponding file paths

Basic Image Retrieval System

Introduction to Image Retrieval

Summary



Basic Image Retrieval System

Manhattan Distance L1



Images Folders



`read_image_from_path`

`folder_to_images`

`absolute_difference`

`Ranking`

Results



Query Image

Basic Image Retrieval System

Manhattan Distance L1

$$L1(\vec{a}, \vec{b}) = \sum_{i=1}^N |a_i - b_i|$$

```
1 def absolute_difference(query, data):  
2     axis_batch_size = tuple(range(1, len(data.shape)))  
3     return np.sum(np.abs(data - query), axis=axis_batch_size)
```

Purpose: This function calculates the sum of absolute differences between a given query and each element in an array **X**, along all dimensions except the first one.

Parameters:

- **query**: A value or array to compare against.
- **X**: An array containing values to compare with **query**.

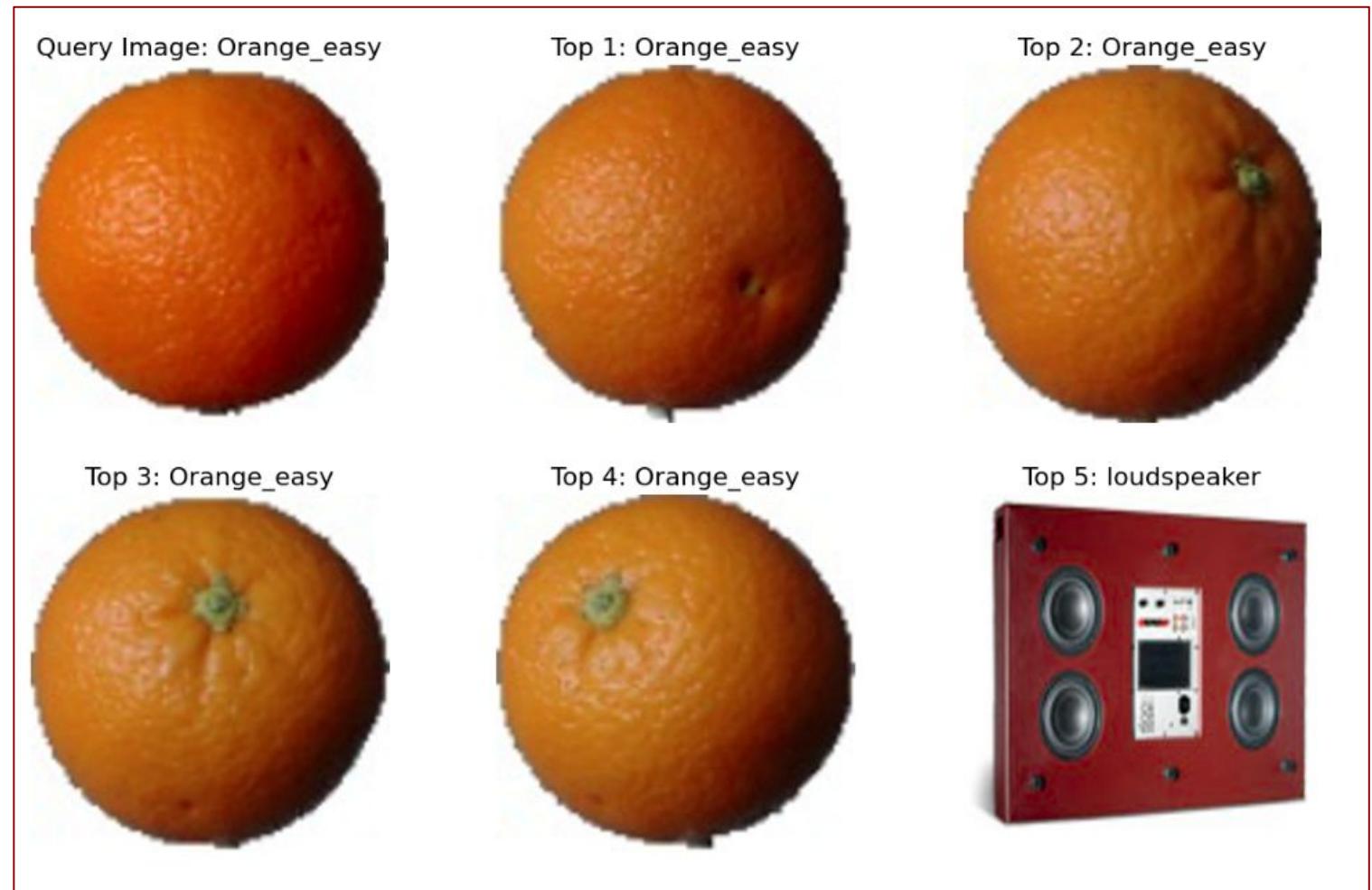
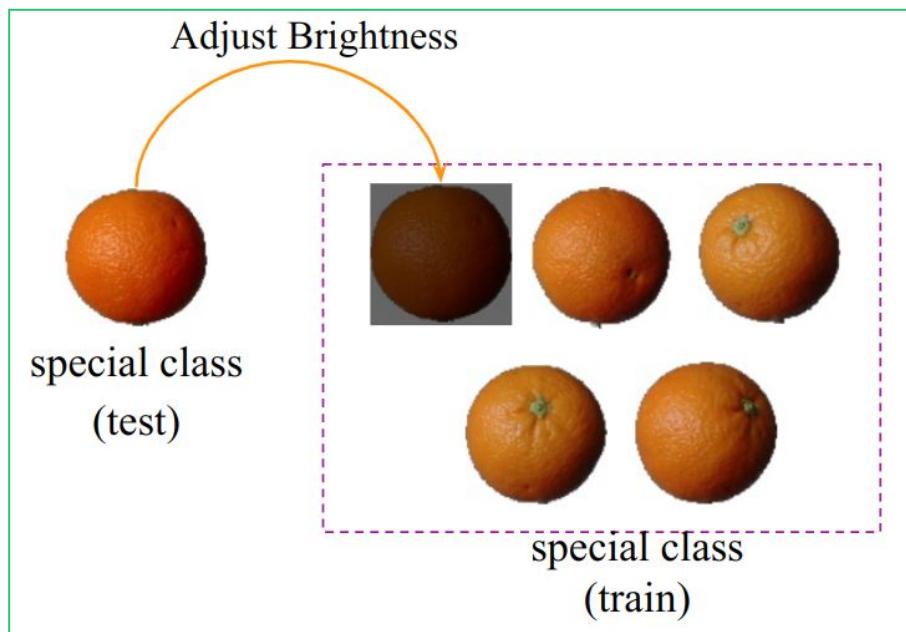
Basic Image Retrieval System

Manhattan Distance L1

```
1 def get_l1_score(root_img_path, query_path, size):
2     query = read_image_from_path(query_path, size)
3     ls_path_score = []
4     for folder in os.listdir(root_img_path):
5         if folder in CLASS_NAME:
6             path = root_img_path + folder
7             images_np, images_path = folder_to_images(path, size) # mang numpy nhieu anh,
8                                         paths
9             rates = absolute_difference(query, images_np)
10            ls_path_score.extend(list(zip(images_path, rates)))
11
12 return query, ls_path_score
```

Basic Image Retrieval System

Manhattan Distance L1



Basic Image Retrieval System

Manhattan Distance L1

Query Image: African_crocodile



Top 1: barn_spider



Top 2: American_egret



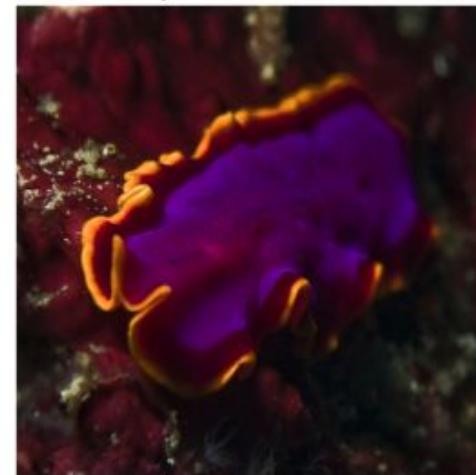
Top 3: ambulance



Top 4: kit_fox



Top 5: flatworm



Basic Image Retrieval System

Euclidean Distance L2



Images Folders

folder_to_images



read_image_from_path

mean_square_difference

Ranking



Results

Basic Image Retrieval System

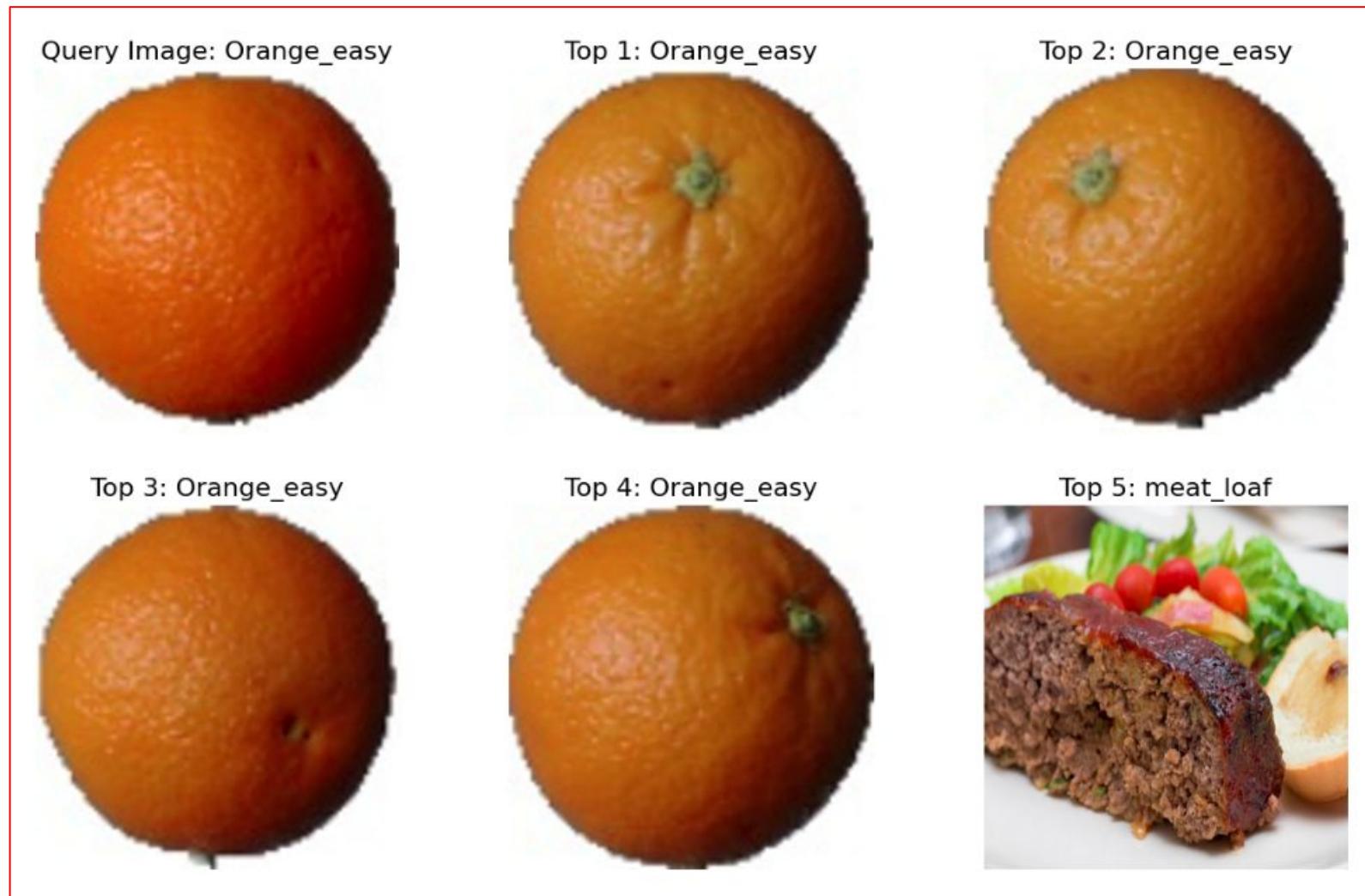
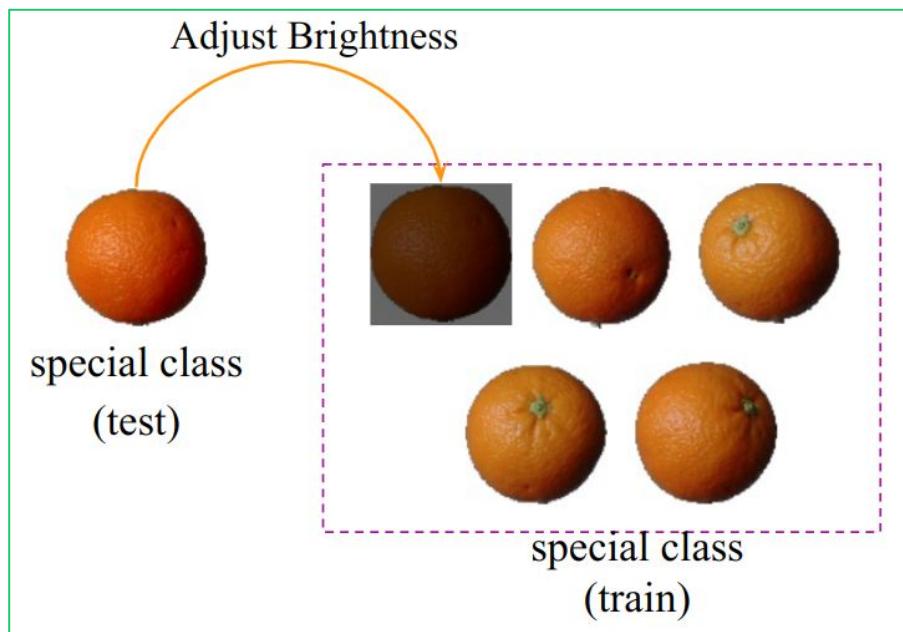
Euclidean Distance L2

$$L2(\vec{a}, \vec{b}) = \sqrt{\sum_{i=1}^N (a_i - b_i)^2}$$

```
1 def mean_square_difference(query, data):  
2     axis_batch_size = tuple(range(1, len(data.shape)))  
3     return np.mean((data - query)**2, axis=axis_batch_size)
```

Basic Image Retrieval System

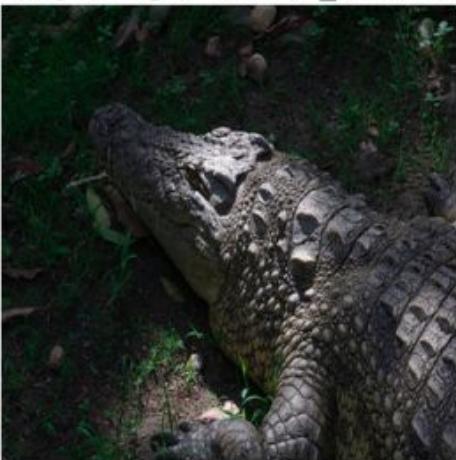
Euclidean Distance L2



Basic Image Retrieval System

Euclidean Distance L2

Query Image: African_crocodile



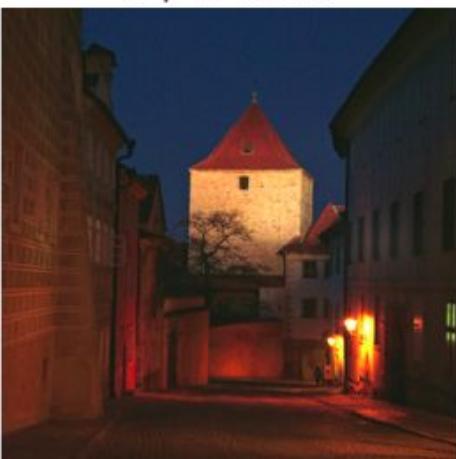
Top 1: American_egret



Top 2: kit_fox



Top 3: castle



Top 4: vine_snake



Top 5: barn_spider



Basic Image Retrieval System

Cosine Similarity



Images Folders

folder_to_images



read_image_from_path

cosine_similarity

Ranking

Results



Query Image

Basic Image Retrieval System

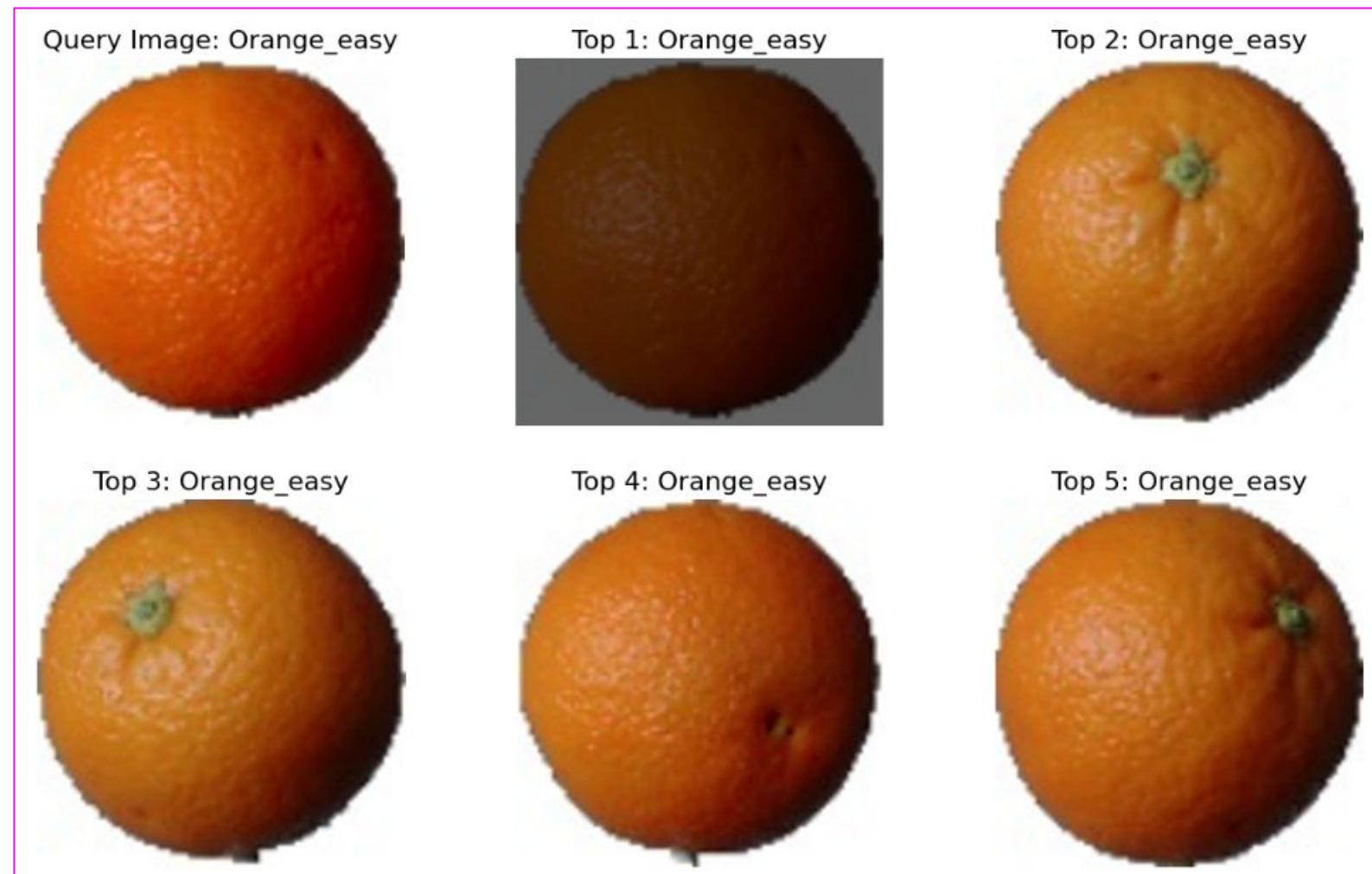
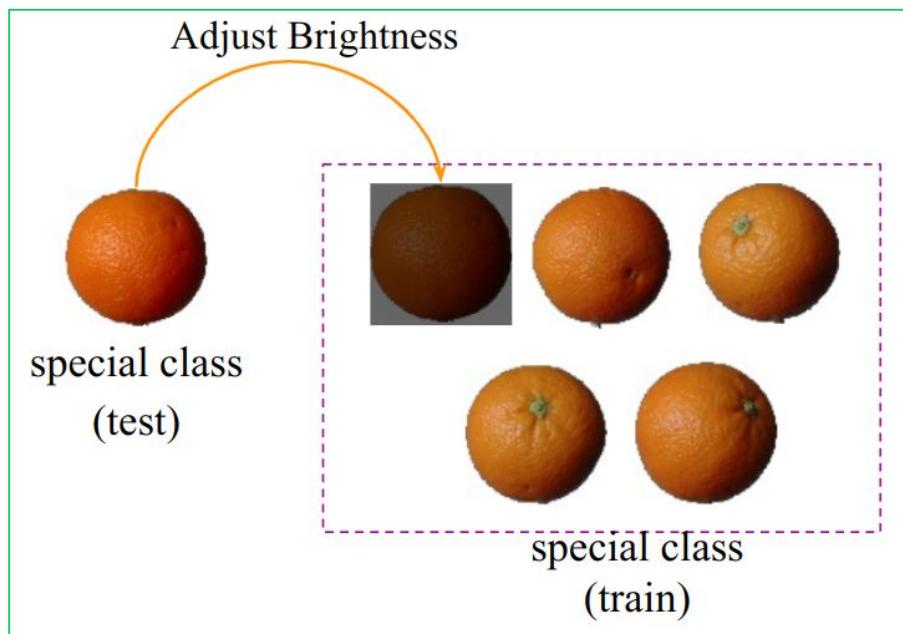
Cosine Similarity

$$\text{cosine_similarity}(\vec{a}, \vec{b}) = \frac{\vec{a} \cdot \vec{b}}{\|\vec{a}\| \|\vec{b}\|} = \frac{\sum_{i=1}^N a_i b_i}{\sqrt{\sum_{i=1}^N a_i^2} \sqrt{\sum_{i=1}^N b_i^2}}$$

```
1 def cosine_similarity(query, data):
2     axis_batch_size = tuple(range(1, len(data.shape)))
3     query_norm = np.sqrt(np.sum(query**2))
4     data_norm = np.sqrt(np.sum(data**2, axis=axis_batch_size))
5     return np.sum(data * query, axis=axis_batch_size) / (query_norm*data_norm + np.finfo(float).eps)
```

Basic Image Retrieval System

Cosine Similarity



Basic Image Retrieval System

Cosine Similarity

Query Image: African_crocodile



Top 1: black_widow



Top 2: bannister



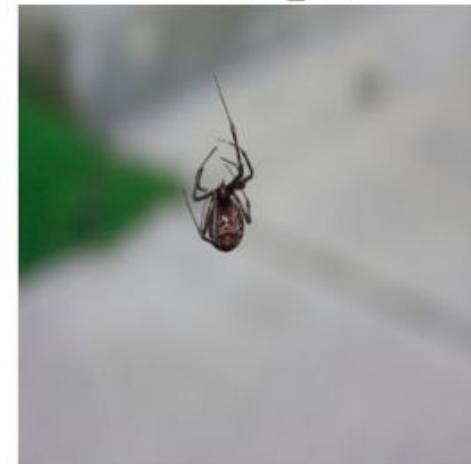
Top 3: flamingo



Top 4: goldfish



Top 5: black_widow



Basic Image Retrieval System

Correlation Coefficient



Images Folders

folder_to_images



read_image_from_path

correlation_coefficient

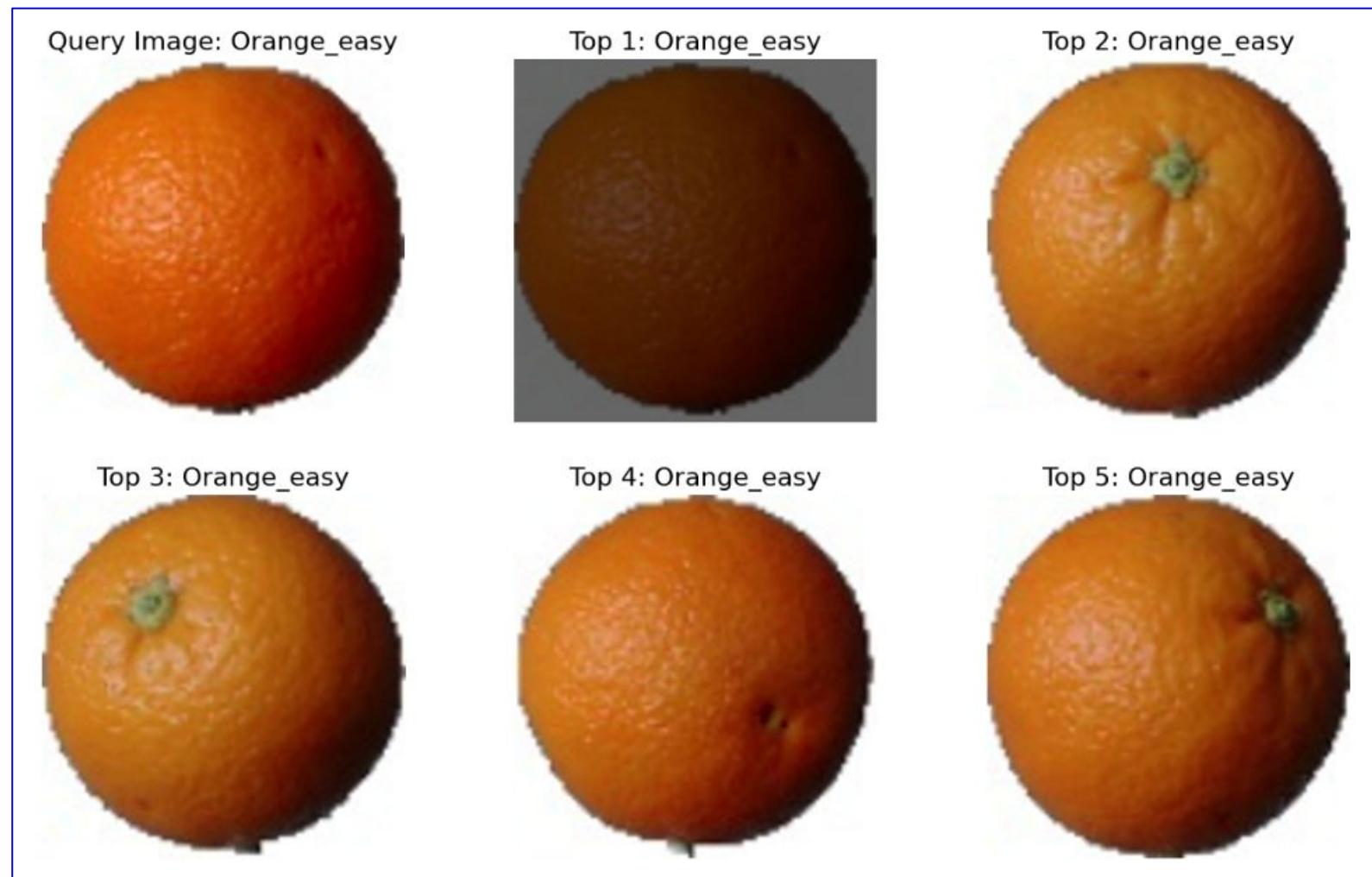
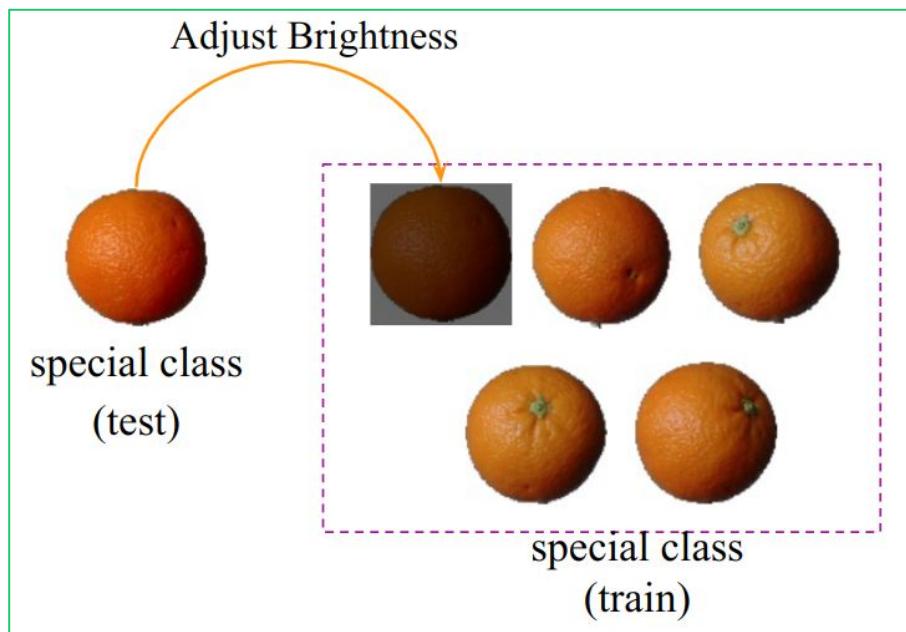
Ranking



Results

Basic Image Retrieval System

Correlation Coefficient



Basic Image Retrieval System

Correlation Coefficient

Query Image: African_crocodile



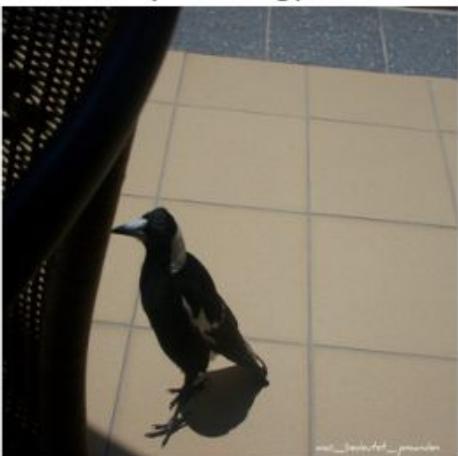
Top 1: bannister



Top 2: black_widow



Top 3: magpie



Top 4: flamingo



Top 5: barn_spider



Basic Image Retrieval System

Trong bài toán truy vấn hình ảnh, khoảng cách L2 (Euclidean distance) trực tiếp trên các giá trị pixel của ảnh thường được sử dụng để:

- A. Đo lường sự khác biệt về hướng giữa các vector pixel của hình ảnh
- B. Tìm kiếm các hình ảnh có hướng vector pixel tương tự nhau
- C. Đo lường sự khác biệt về độ lớn giữa các giá trị pixel của hai hình ảnh
- D. Đo lường sự khác biệt tuyệt đối giữa các vector pixel của hình ảnh

Advanced Image Retrieval Using Pre-trained Deep Learning Model

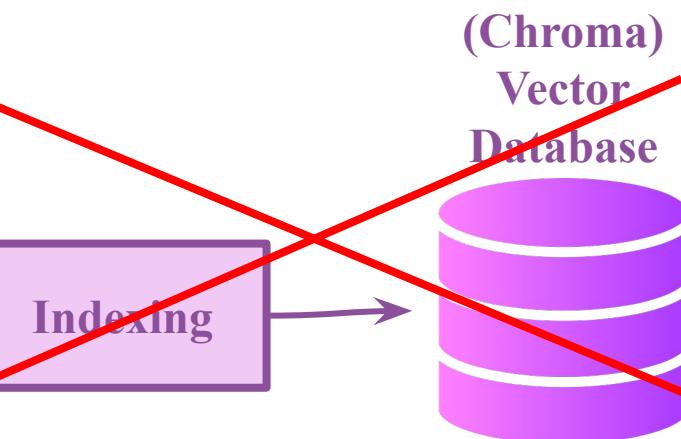
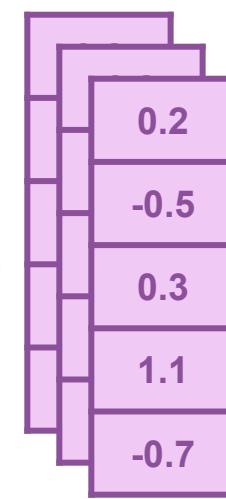
Summary



Images Library

CLIP Model
(Pretrained Model)

Feature Vectors



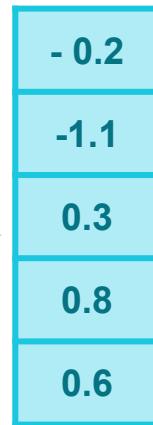
Indexing

(Chroma)
Vector
Database



CLIP Model
(Pretrained Model)

Feature Vector



Similarity
Computation



Ranking

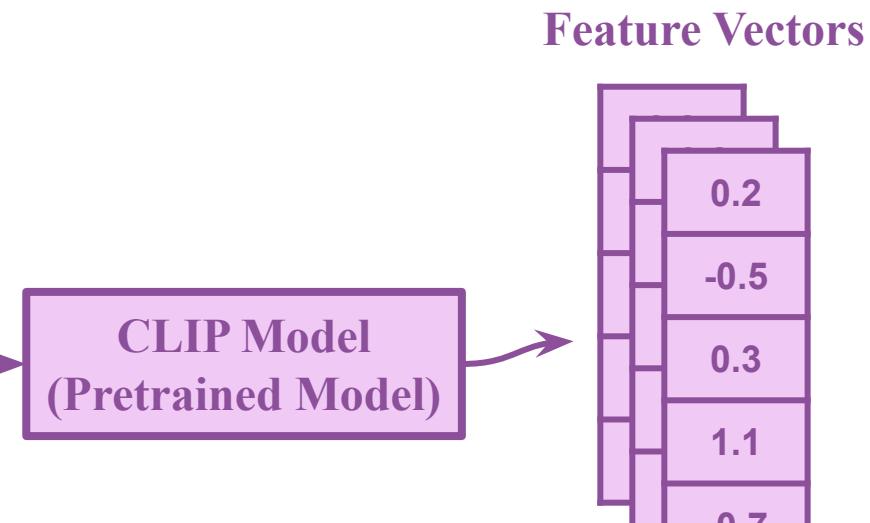
Results

Query Image

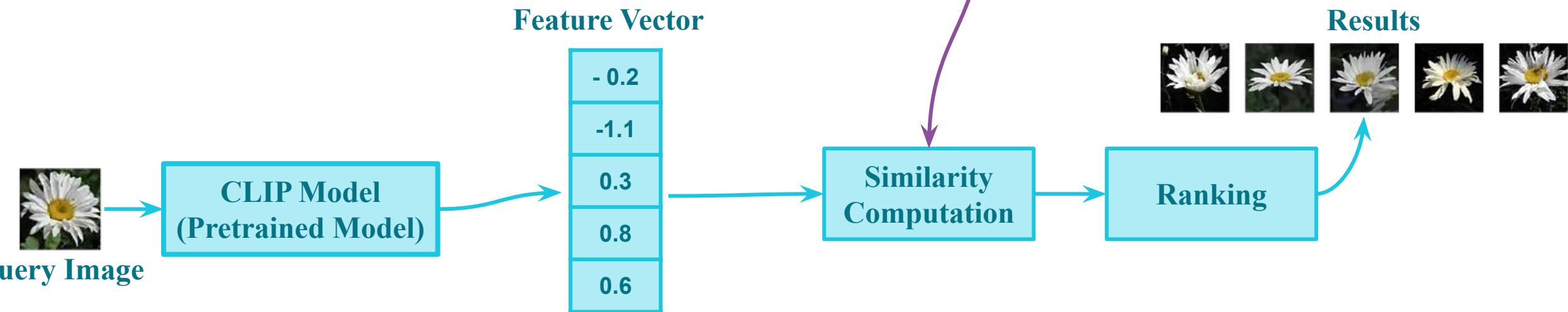
Summary



Images Library

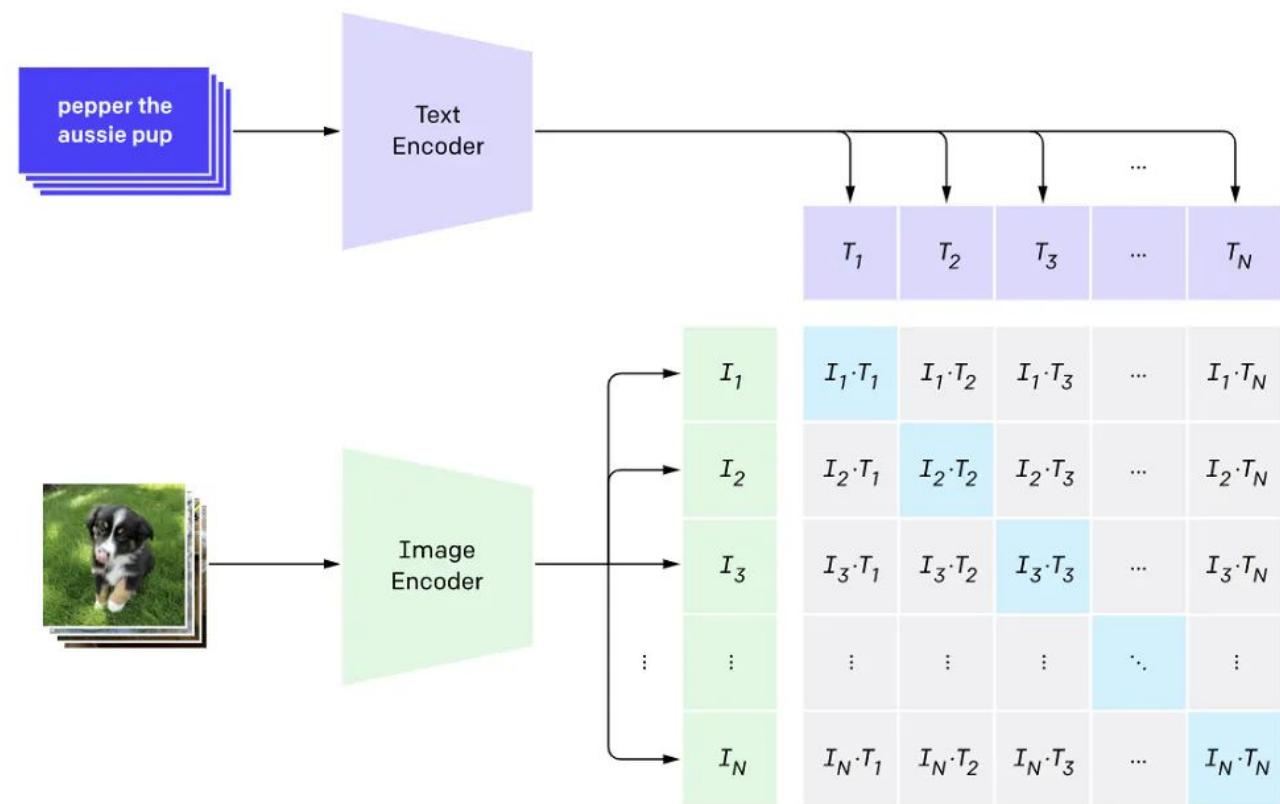


Feature Vectors

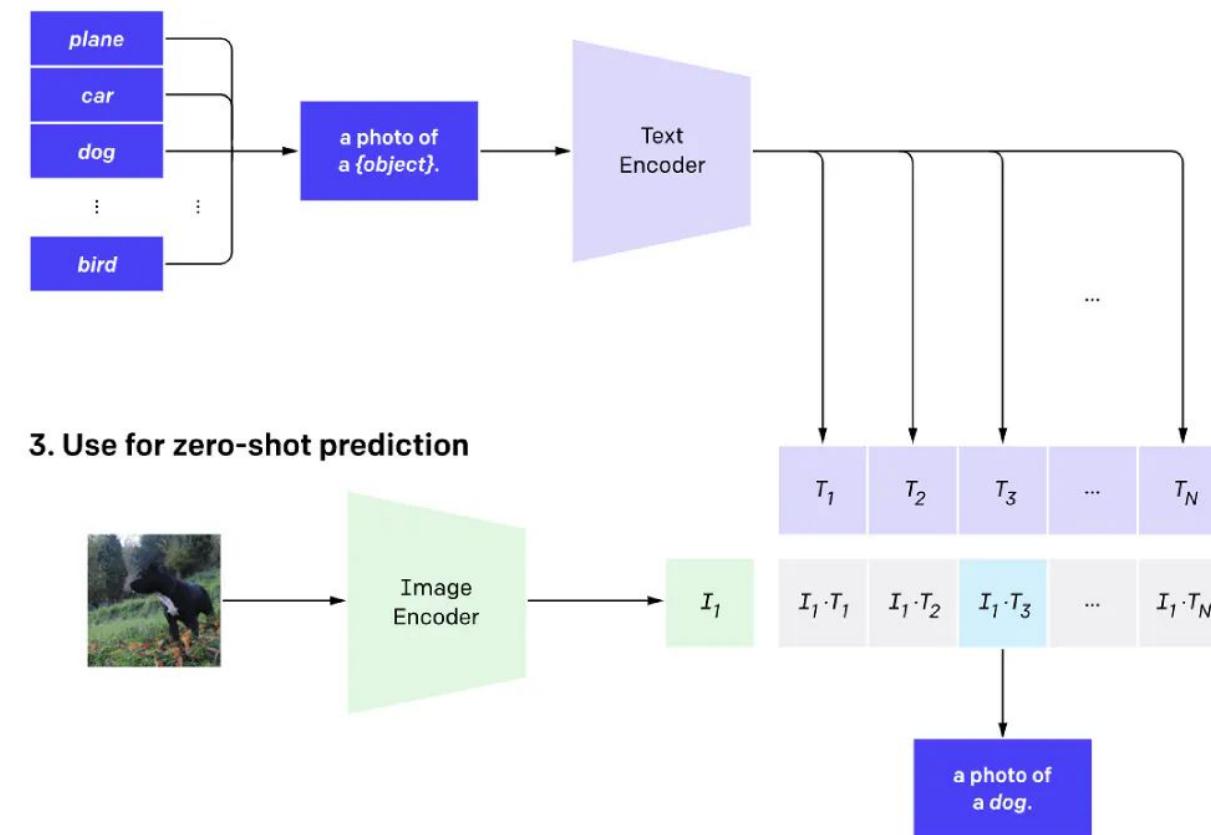


How does the CLIP algorithm work?

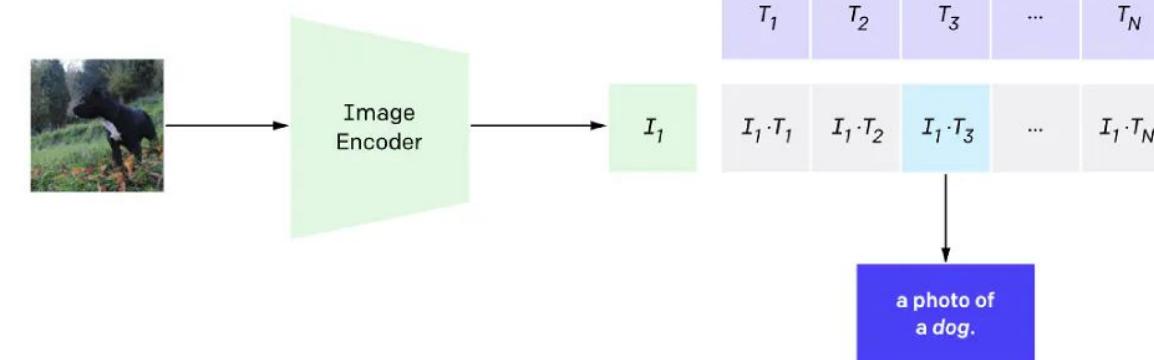
1. Contrastive pre-training



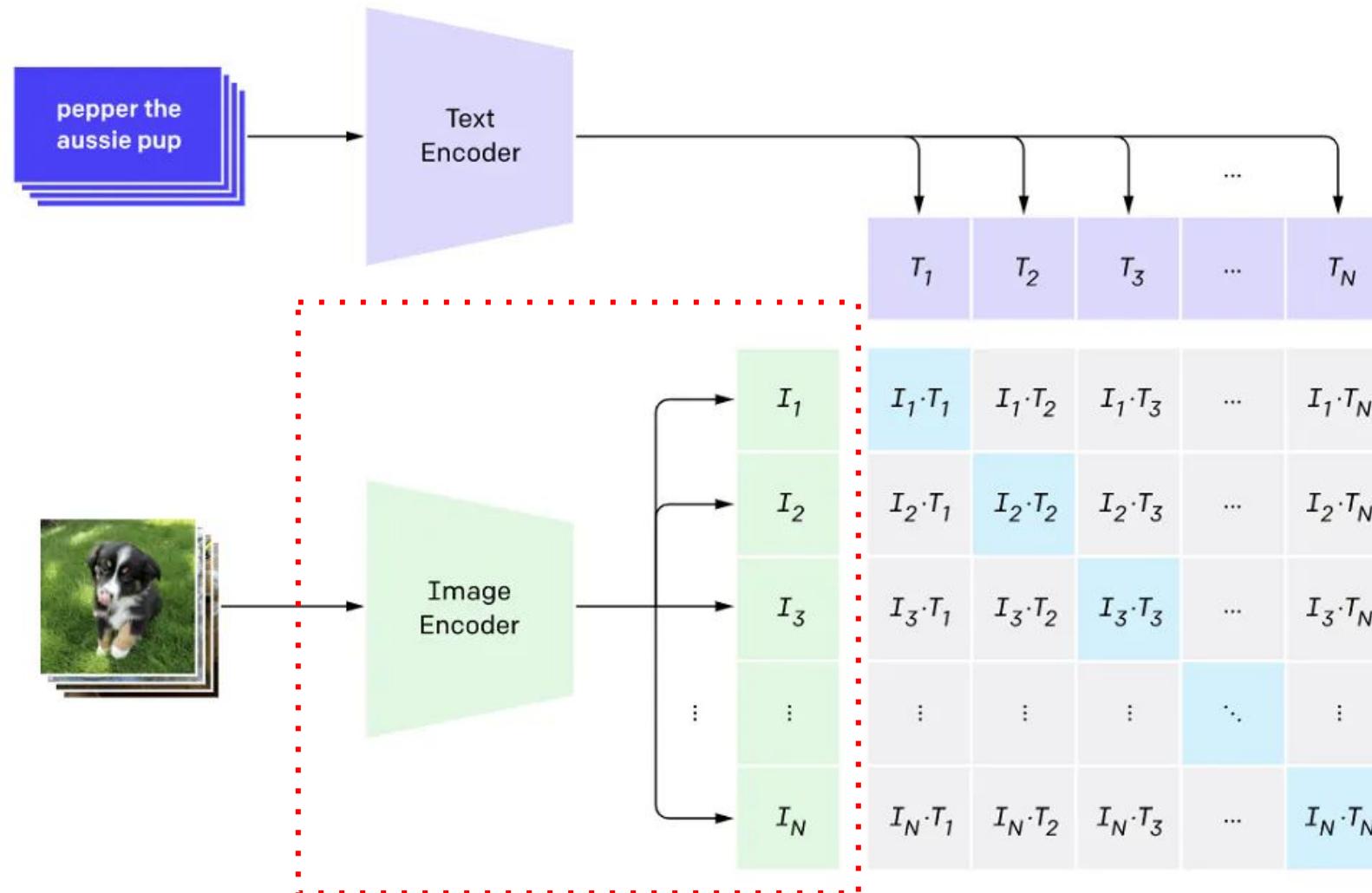
2. Create dataset classifier from label text



3. Use for zero-shot prediction



Get Embeddings with CLIP Model



Get Embeddings with CLIP Model

```
1 pip install chromadb
2 pip install open-clip-torch
8 from chromadb.utils.embedding_functions import OpenCLIPEmbeddingFunction

1 embedding_function = OpenCLIPEmbeddingFunction()
2
3 def get_single_image_embedding(image):
4     embedding = embedding_function._encode_image(image=image)
5     return np.array(embedding)
```

Basic Image Retrieval System

Manhattan Distance L1

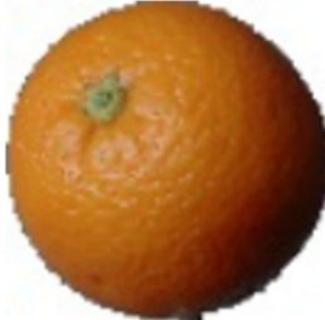
Query Image: Orange_easy



Top 1: Orange_easy



Top 2: Orange_easy



Top 3: Orange_easy



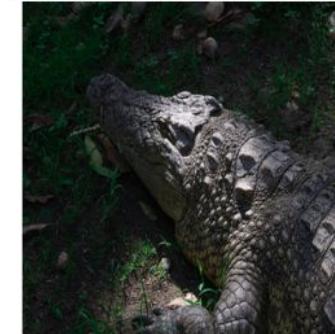
Top 4: Orange_easy



Top 5: Orange_easy



Query Image: African_crocodile



Top 1: African_crocodile



Top 2: African_crocodile



Top 3: African_crocodile



Top 4: African_crocodile



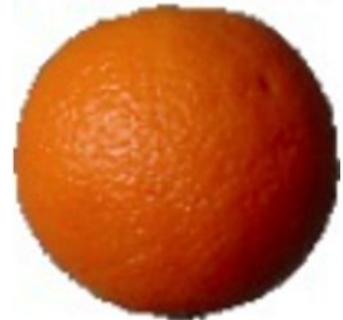
Top 5: African_crocodile



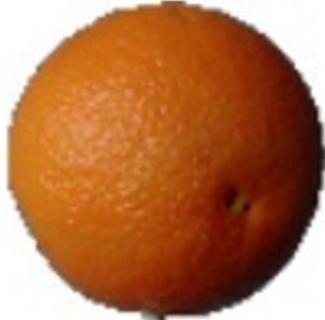
Basic Image Retrieval System

Euclidean Distance L2

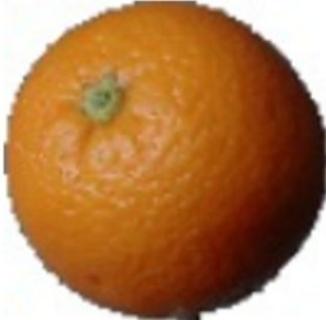
Query Image: Orange_easy



Top 1: Orange_easy



Top 2: Orange_easy



Top 3: Orange_easy



Top 4: Orange_easy



Top 5: Orange_easy



Query Image: African_crocodile



Top 1: African_crocodile



Top 2: African_crocodile



Top 3: African_crocodile



Top 4: African_crocodile



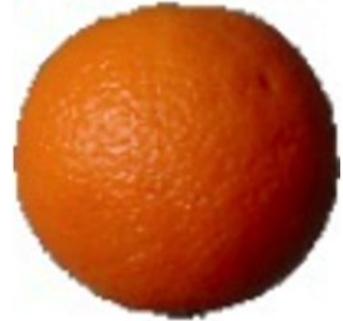
Top 5: African_crocodile



Basic Image Retrieval System

Cosine Similarity

Query Image: Orange_easy



Top 1: Orange_easy



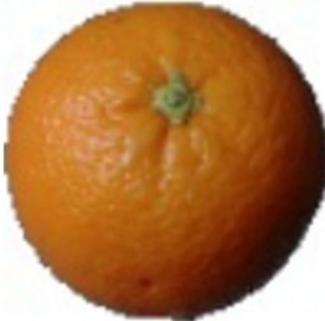
Top 2: Orange_easy



Top 3: Orange_easy



Top 4: Orange_easy



Top 5: Orange_easy



Query Image: African_crocodile



Top 1: African_crocodile



Top 2: African_crocodile



Top 3: African_crocodile



Top 4: African_crocodile



Top 5: African_crocodile



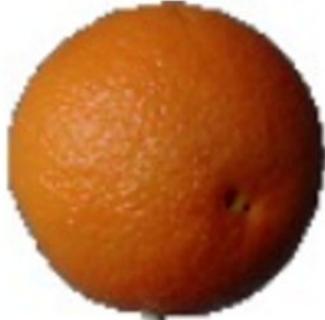
Basic Image Retrieval System

Correlation Coefficient

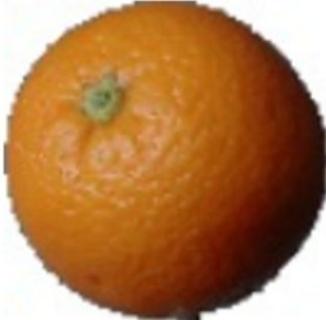
Query Image: Orange_easy



Top 1: Orange_easy



Top 2: Orange_easy



Top 3: Orange_easy



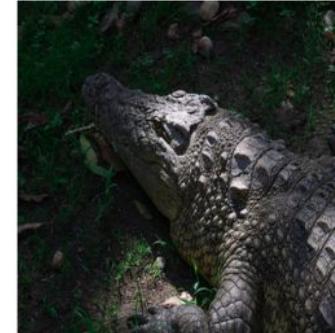
Top 4: Orange_easy



Top 5: Orange_easy



Query Image: African_crocodile



Top 1: African_crocodile



Top 2: African_crocodile



Top 3: African_crocodile



Top 4: African_crocodile



Top 5: African_crocodile



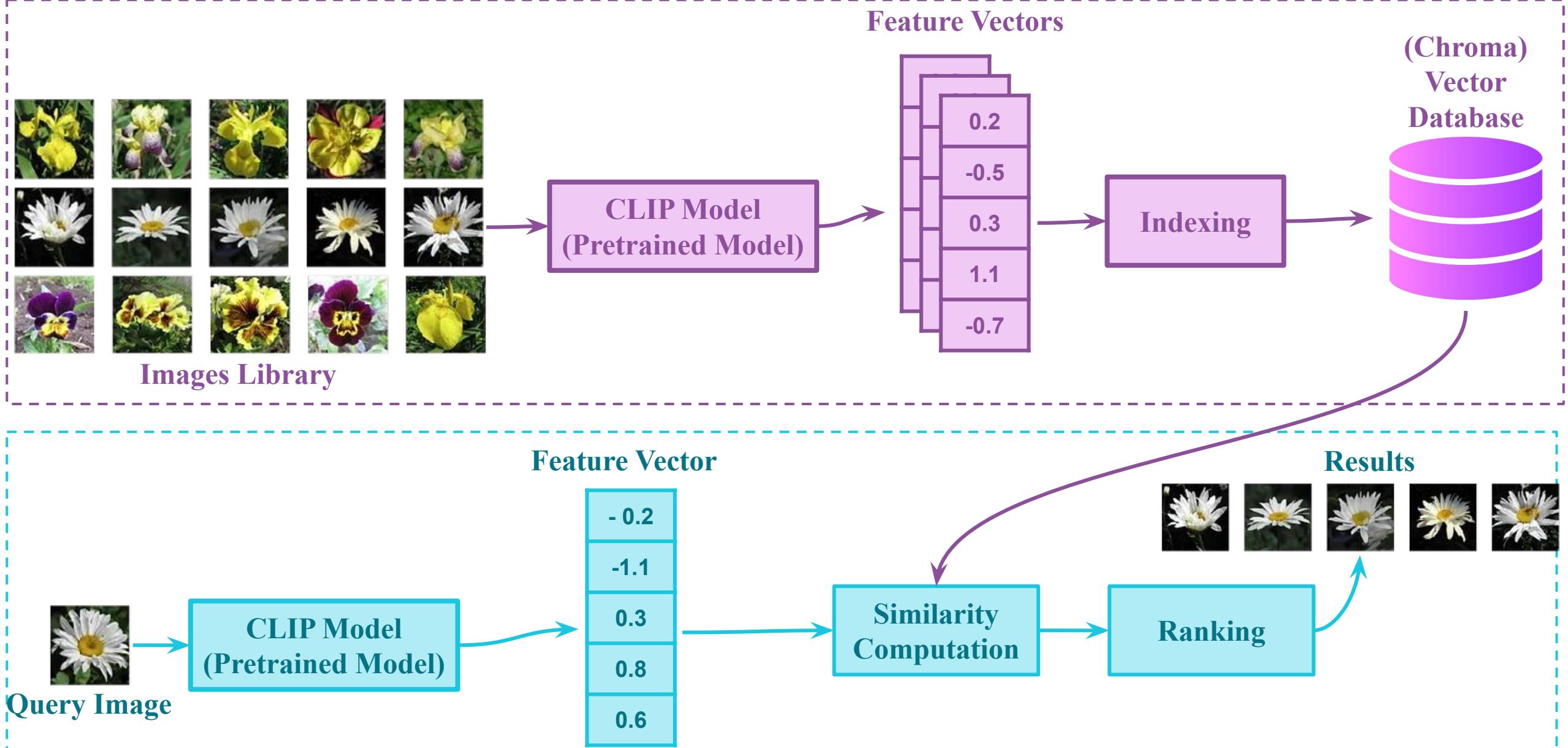
QUIZ

<time>



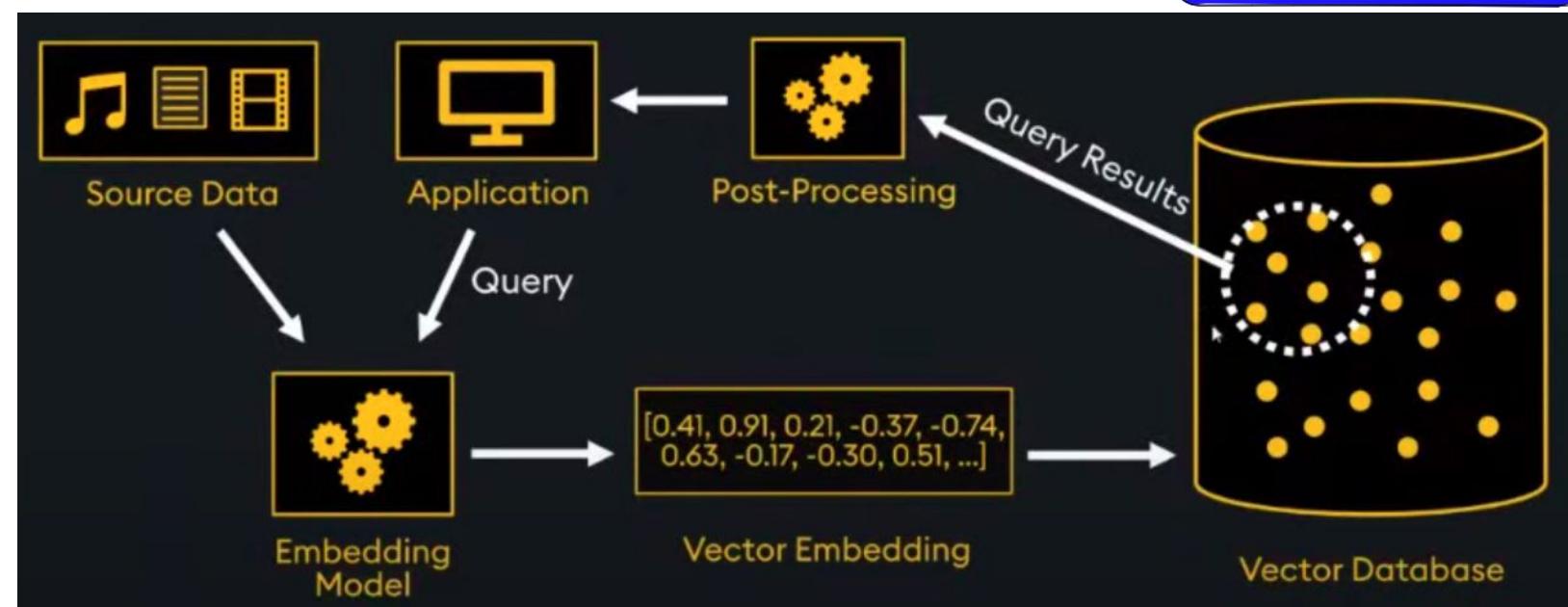
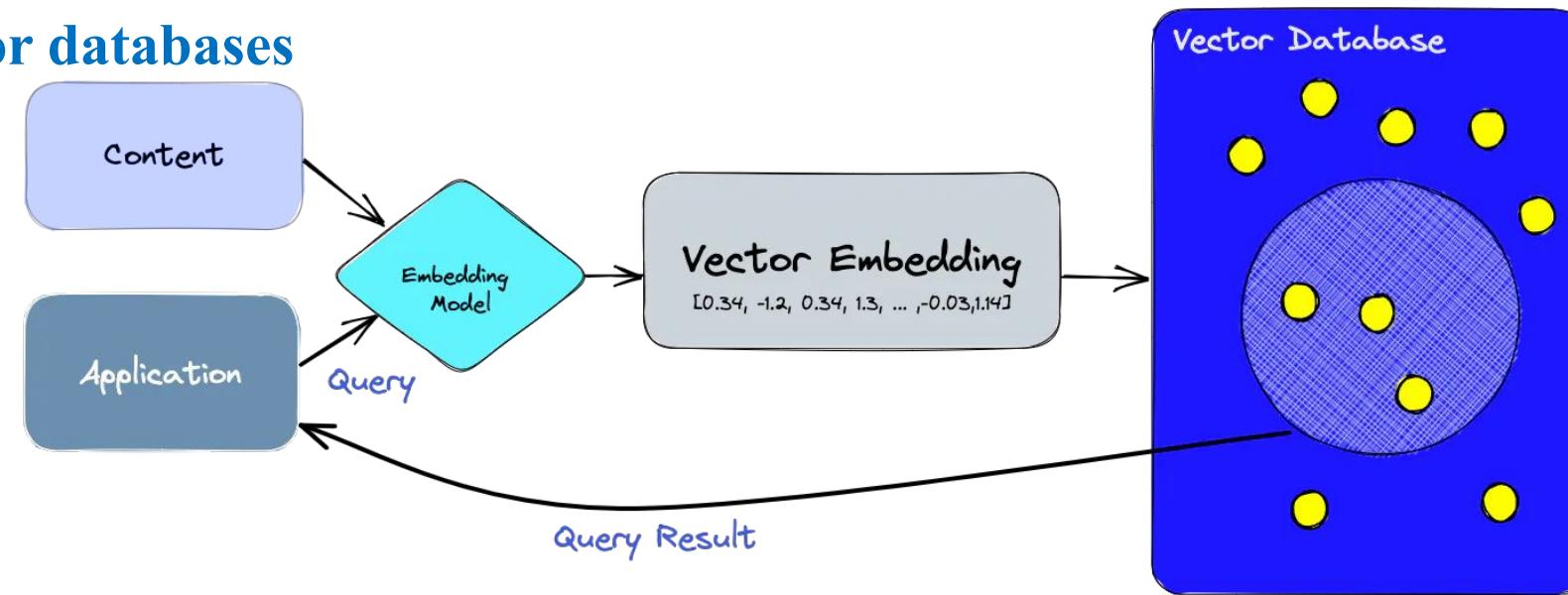
Implementing Image Retrieval with Vector Database

Implementing Image Retrieval with Vector Database



Implementing Image Retrieval with Vector Database

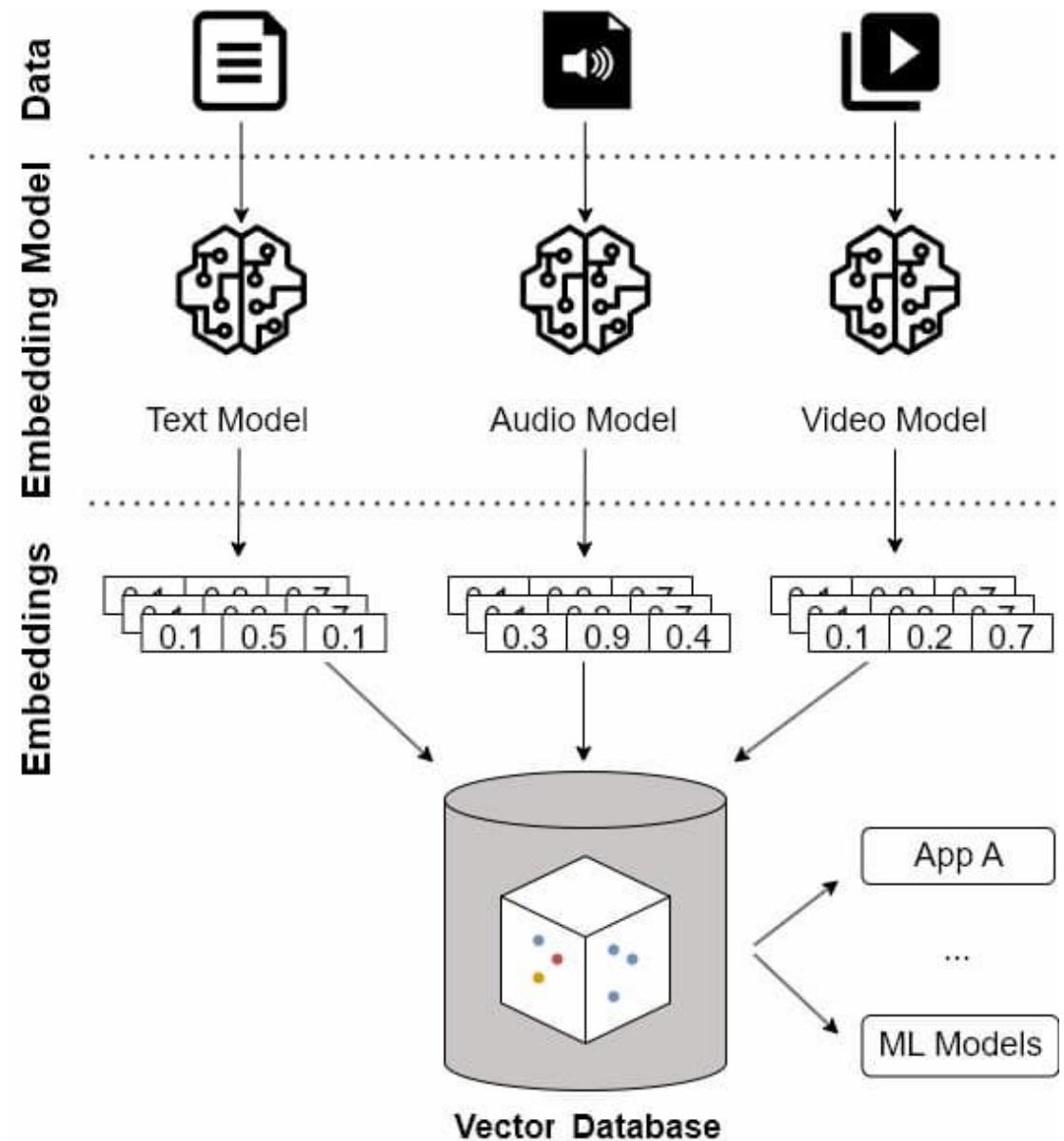
Overview of vector databases



Overview of vector databases

A **vector database** is a specialized database for storing, searching, and managing information as vectors, which are the numerical representation of objects in a high-dimensional space (e.g., documents, text, images, videos, audio) that capture certain features of the object itself. This numerical representation is called a **vector embedding**

- Designed for scenarios where understanding the context, similarity, or pattern is **more important** than matching exact values
- Data is organized by leveraging mathematics of vectors, and principles of geometry



Overview of vector databases

Vector Embeddings:

- Created using ML models.
- Translate semantic and qualitative values into numerical representations.
- Different ML models for different data types (text, audio, image).

Vector Databases:

- Suitable for high concurrency and large data volumes.
- Support embedding associations with object metadata.

Benefits:

- Makes vector databases integrable, versatile, and interpretable.
- Similar querying capabilities to traditional databases.

Metadata Association:

- Can include structured and object definitions.
- Enables sophisticated querying and filtering.
- Facilitates better management and integration with data architectures.

Query Processor

Interface

Queries

Attribute k-NN ANN Hybrid

Data Manip. Range Batch Multi.

Operators

Ins Up Del Sort / Top-K Table Scan
Embed Proj Idx Scan Hybrid Scan

Query Optimizer

Query Executor

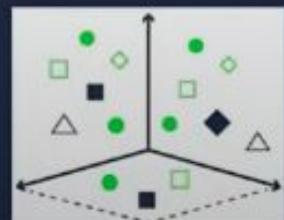
Storage Manager

Search Indexes

LSH IVF k-d RP KGraph EFANNA NSG
L2H FLANN ANNOY FANNG HNSW NGT

Vector Storage

Vector DBs convert data into vectors...



[0.23, 0.45, ..., 0.84, 0.23],

[0.63, 0.32, ..., 0.34, 0.92]

Images: EXIF metadata

- Added by camera
 - Or post-processing software
- JPEG or HEIC

General	Exif	GPS	TIFF
Altitude	184,47 m (605,2 ft)		
Altitude Reference	above sea level		
Destination Bearing	21,327		
Destination Bearing Reference	True direction		
Horizontal Positioning Error	17,226		
Image Direction	21,327		
Image Direction Reference	True north		
Latitude	44° 43' 38,772" N		
Longitude	5° 1' 17,07" E		
Speed	0		
Speed Reference	Kilometers per hour		

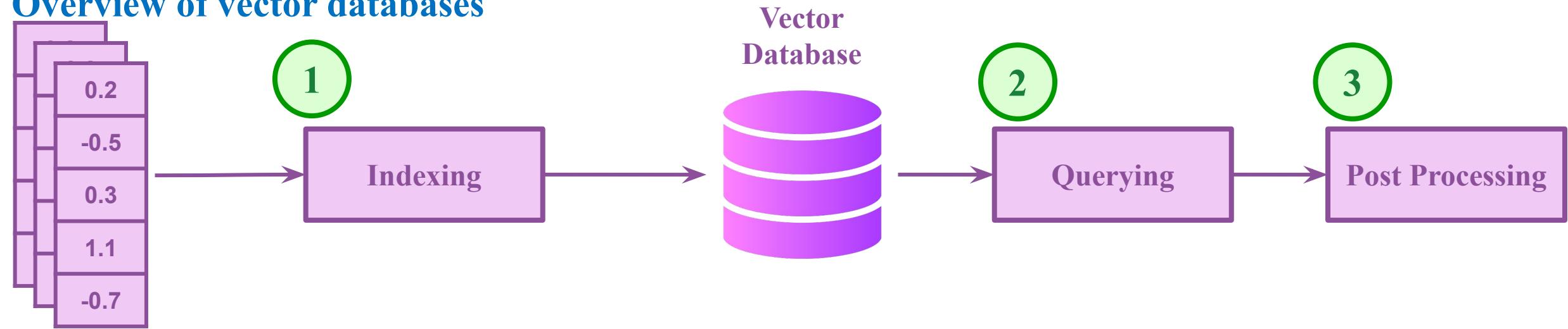
General	Exif	GPS	TIFF
Aperture Value	2		
Brightness Value	1,082		
Color Space	Uncalibrated		
Components Configuration	1, 2, 3, 0		
CompositelImage	2		
Date Time Digitized	9 Aug 2023 at 21:15:18		
Date Time Original	9 Aug 2023 at 21:15:18		
Digital Zoom Ratio	1,217		
Exif Version	2.3.2		
Exposure Bias Value	0		
Exposure Mode	Auto exposure		
Exposure Program	Normal program		
Exposure Time	1/50		
Flash	Off, did not fire		
FlashPix Version	1.0		
FNumber	2		
Focal Length	6		
Focal Length In 35mm Film	63		
Photographic Sensitivity	400		
Lens Make	Apple		
Lens Model	iPhone 11 Pro back trip...		
Lens Specification	1,54, 6, 1,8, 2,4		
Metering Mode	Pattern		
Time Zone for Modification	+02:00		
Time Zone for Digitization	+02:00		
Time Zone for Original Date	+02:00		
Pixel X Dimension	4032		
Pixel Y Dimension	3024		
Scene Capture Type	Standard		
Scene Type	A directly photographed scene		
Sensing Method	One-chip color area sensor		
Shutter Speed Value	1/50		
Subject Area	2022, 1515, 2329, 1395		
Sub-second Time Digitized	527		
Sub-second Time Original	527		
White Balance	Auto white balance		



This is the village I live in!

Implementing Image Retrieval with Vector Database

Overview of vector databases



- 1. Indexing:** The vector database indexes vectors using an algorithm such as PQ, LSH, or HNSW. This step maps the vectors to a data structure that will enable faster searching.
- 2. Querying:** The vector database compares the indexed query vector to the indexed vectors in the dataset to find the nearest neighbors (applying a similarity metric used by that index)
- 3. Post Processing:** In some cases, the vector database retrieves the final nearest neighbors from the dataset and post-processes them to return the final results. This step can include re-ranking the nearest neighbors using a different similarity measure.

Overview of vector databases

Embedding representation

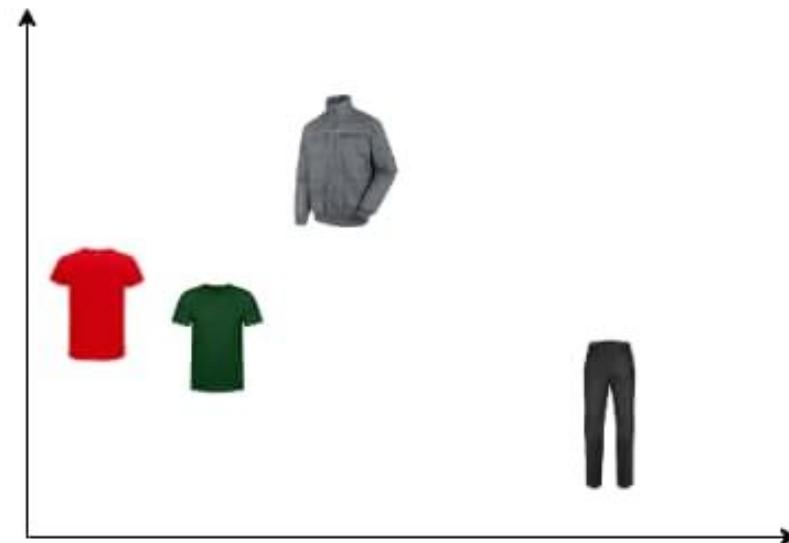


0.46	-0.30	1.20	0.65
------	-------	------	------

Array of embeddings

	0.45	0.32
	0.46	0.30
	0.70	0.88
	2	1.45

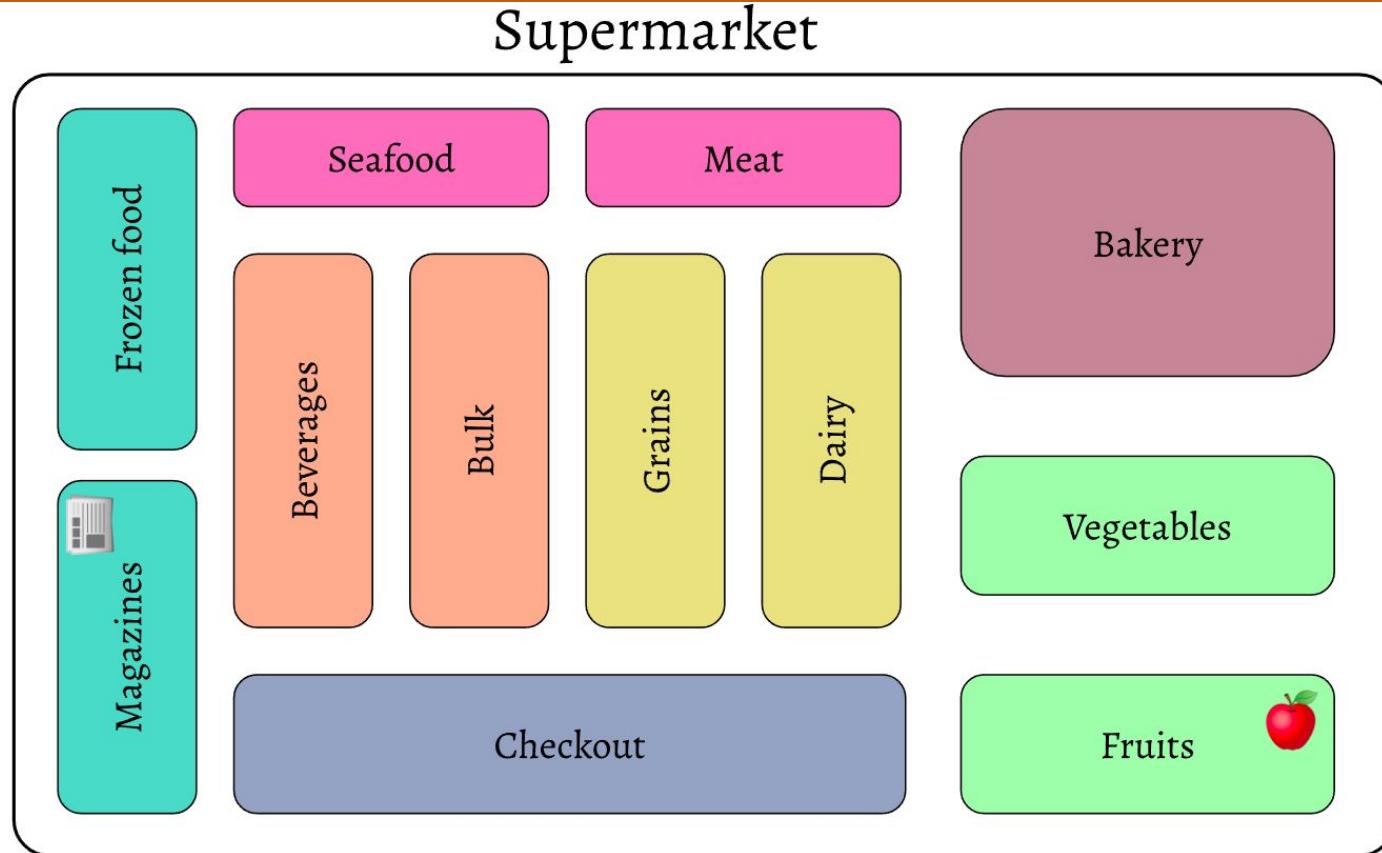
Dimensional map



The number of **dimensions** in embeddings is **crucial** because each dimension represents a feature of the object, captured as a numerical value. While more dimensions can **enhance accuracy**, they also require **more computational resources**, including memory, latency, and cost.

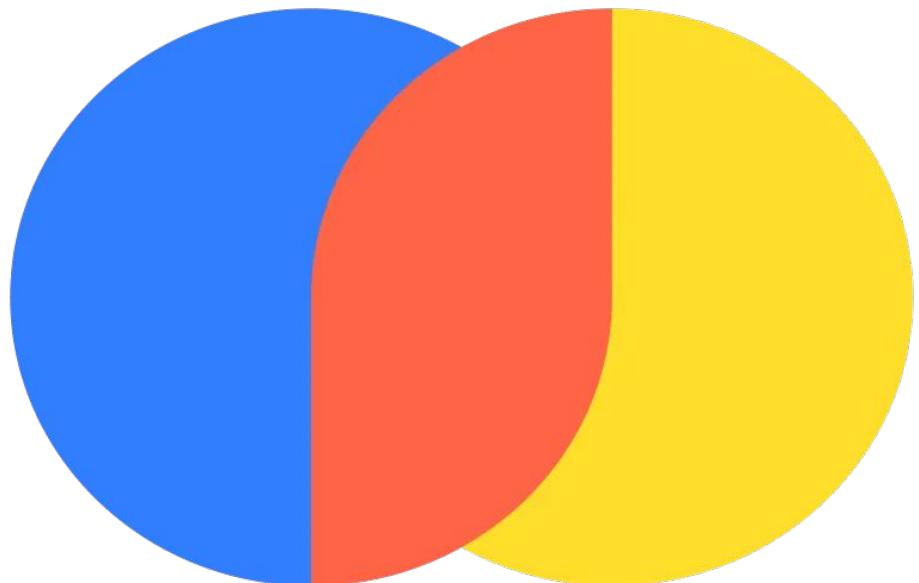
- T-shirts are close to each other due to being the same product with different colors.
- The jacket is near the T-shirts because they share attributes like sleeves and a collar.
- Jeans are the furthest to the right, as they do not share attributes with the other products.

Vector Indexes



- **Definition:** Specialized data structures for efficiently storing, organizing, and querying high-dimensional vector embeddings.
- **Purpose:** Provide fast and cost-effective search queries.
- **Examples:** Approximate nearest neighbor, Inverted index, Locality-sensitive hashing

Chroma Vector Database



Embeddings made easy

Chroma has all the tools you need to use embeddings

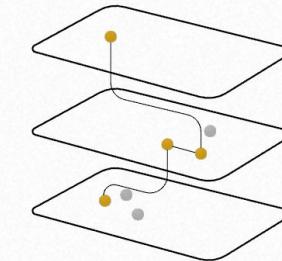
Simple

As easy as `pip install`, use in a notebook in 5 seconds

```
> pip install chromadb
```

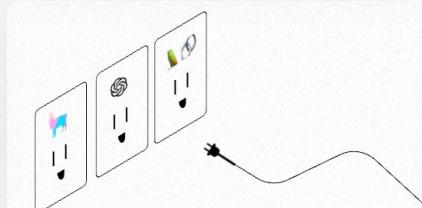


```
import chromadb  
  
client = chromadb.Client()  
  
c = client.create_collection("test")  
  
# add embeddings and documents  
c.add(...)  
  
# get back similar ones  
c.query(...)
```



Feature-rich

Search, filtering, and more



Integrations

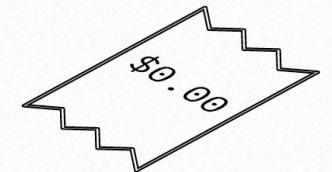
Plugs right in to LangChain, LlamaIndex, OpenAI and others

JavaScript Client

`npm install chromadb` and it ships with `@types`

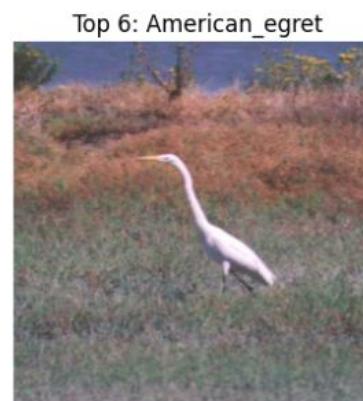
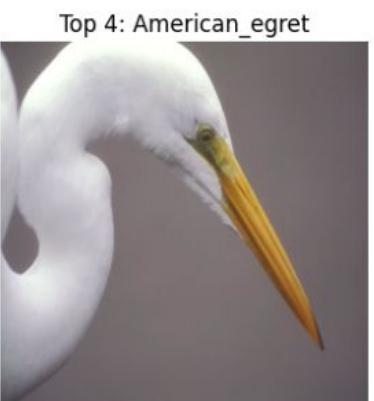
Free

Apache 2.0 and open source



Vector Indexes

Euclidean Distance L2



Cosine Similarity



Basic Image Retrieval System

Khi sử dụng vector database trong bài toán truy vấn hình ảnh, việc lưu trữ và truy xuất các vector đặc trưng của hình ảnh cho phép:

- A. So sánh trực tiếp các giá trị pixel của hình ảnh
- B. Tăng tốc quá trình tìm kiếm các hình ảnh tương tự bằng cách so sánh các vector đặc trưng thay vì các hình ảnh gốc
- C. Đo lường sự khác biệt về độ lớn giữa các hình ảnh gốc
- D. Phân loại các hình ảnh gốc dựa trên kích thước của chúng

Summary

- ✓ Introduce the concept of image retrieval and its applications.
- ✓ Discuss various similarity measurement techniques used in image retrieval.
- ✓ Outline the process of data preparation for image retrieval tasks.
- ✓ Demonstrate how to build a basic image retrieval system.
- ✓ Explore advanced image retrieval methods using pre-trained deep learning models.
- ✓ Explain the implementation of image retrieval with vector databases.
- ✓ (Optional) Provide an overview of data acquisition through web crawling.



vector techniques databases implementation introduce web preparation used provide pre-trained acquisition using measurement various basic explain explore

optional crawling outline build

learning

retrieval

image

process methods advanced deep discuss overview

similarity

data

concept

system models tasks

demonstrate

