Introduction to Vision-Language Models

BIODS 271 / CS 277

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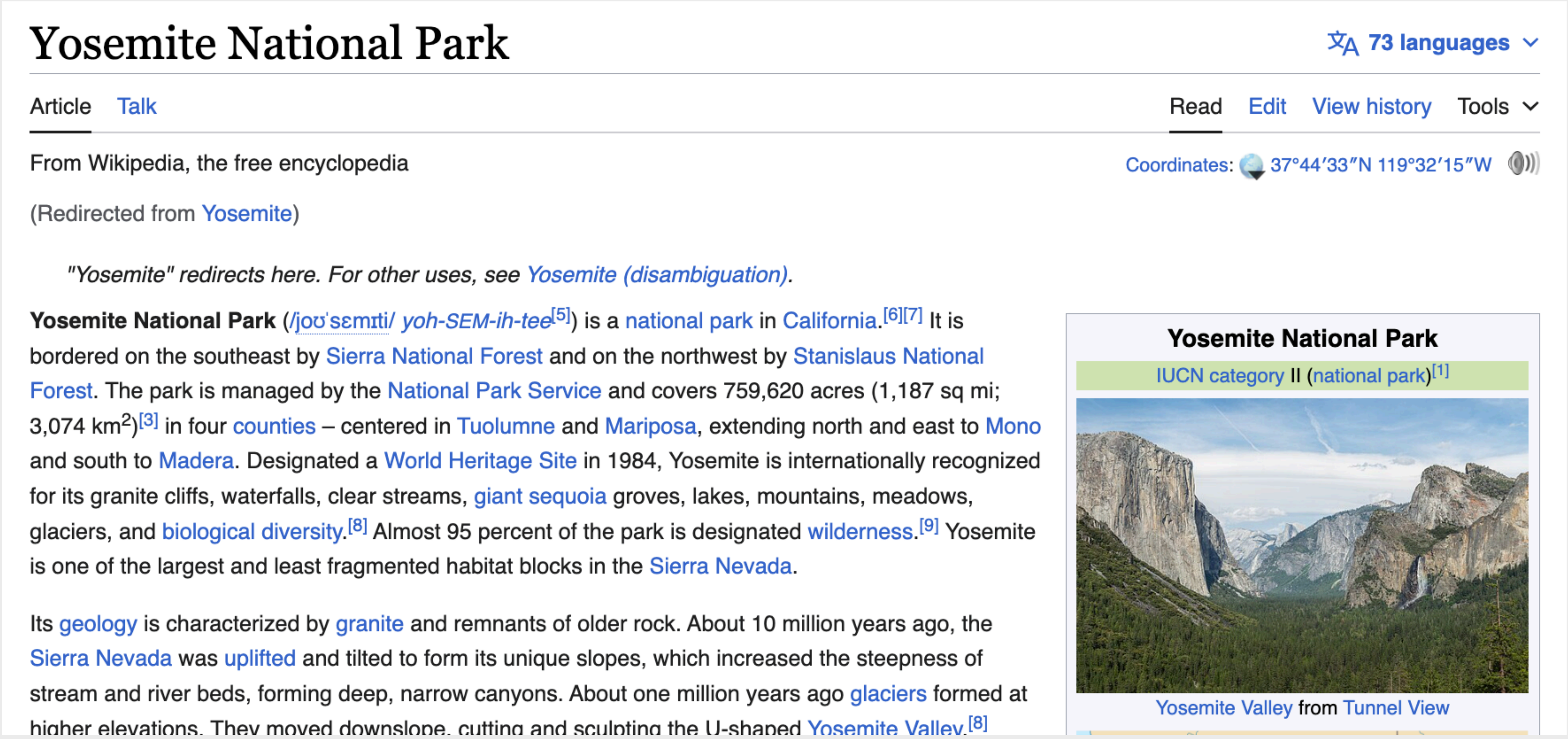
Stanford University

Attendance Code

`multimodal`

Why do we need VLMs?

The human experience of the world is multimodal, so we need AI systems capable of simultaneously processing diverse input modalities



Yosemite National Park

From Wikipedia, the free encyclopedia

Coordinates: 37°44′33″N 119°32′15″W

(Redirected from Yosemite)

"Yosemite" redirects here. For other uses, see Yosemite (disambiguation).

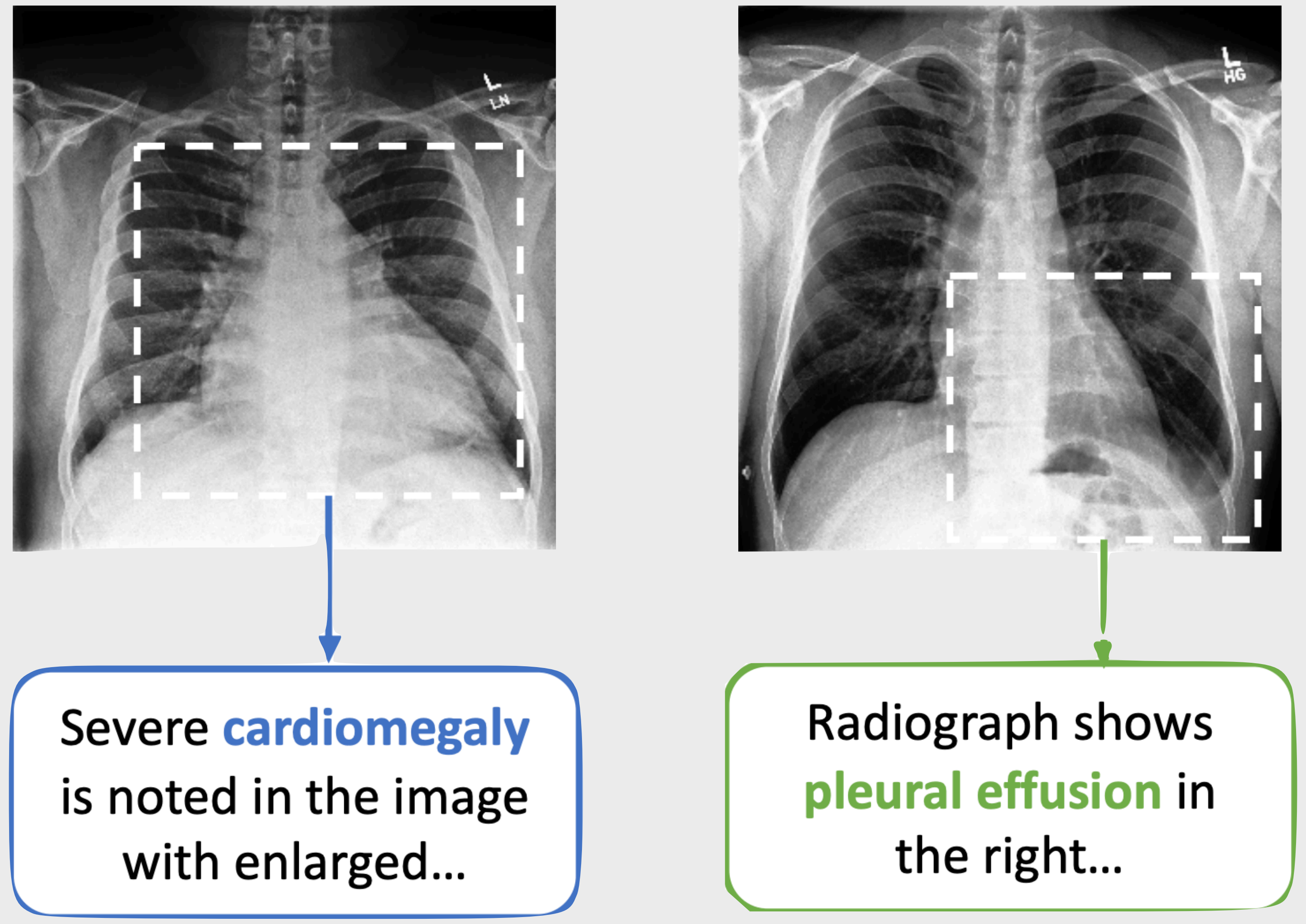
Yosemite National Park (/joʊˈsɛmɪti/ *yoh-SEM-ih-tee*[5]) is a national park in California.[6][7] It is bordered on the southeast by Sierra National Forest and on the northwest by Stanislaus National Forest. The park is managed by the National Park Service and covers 759,620 acres (1,187 sq mi; 3,074 km^2)[3] in four counties – centered in Tuolumne and Mariposa, extending north and east to Mono and south to Madera. Designated a World Heritage Site in 1984, Yosemite is internationally recognized for its granite cliffs, waterfalls, clear streams, giant sequoia groves, lakes, mountains, meadows, glaciers, and biological diversity.[8] Almost 95 percent of the park is designated wilderness.[9] Yosemite is one of the largest and least fragmented habitat blocks in the Sierra Nevada.

Its geology is characterized by granite and remnants of older rock. About 10 million years ago, the Sierra Nevada was uplifted and tilted to form its unique slopes, which increased the steepness of stream and river beds, forming deep, narrow canyons. About one million years ago glaciers formed at higher elevations. They moved downslope, cutting and sculpting the U-shaped Yosemite Valley.[8]

Yosemite National Park

IUCN category II (national park)[1]

Yosemite Valley from Tunnel View



Severe **cardiomegaly** is noted in the image with enlarged...

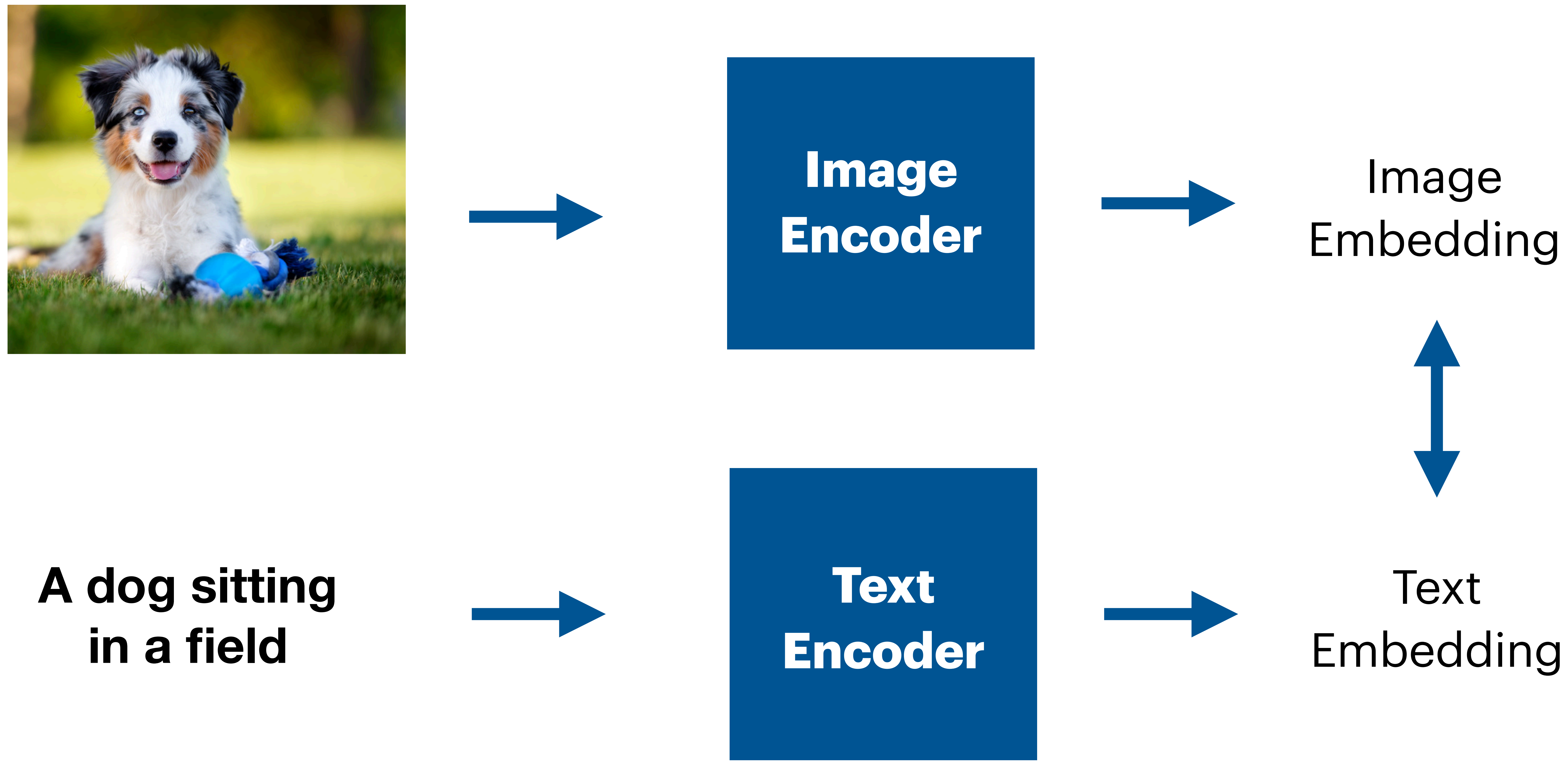
Radiograph shows **pleural effusion** in the right...

Data is often inherently multimodal

Part 1: Pretraining Methods and Datasets

Contrastive Language-Image Pretraining (CLIP)

Key Idea: Maximize the similarity between true image-text embedding pairs and minimize similarity between mismatched image-text embedding pairs



A dog sitting in a field

Image Encoder

Text Encoder

Image Embedding

Text Embedding

Radford et al. "Learning Transferable Visual Models From Natural Language Supervision”

Contrastive Language-Image Pretraining (CLIP)

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A dog sitting in a field

Batch with N image-caption pairs

Radford et al. "Learning Transferable Visual Models From Natural Language Supervision”

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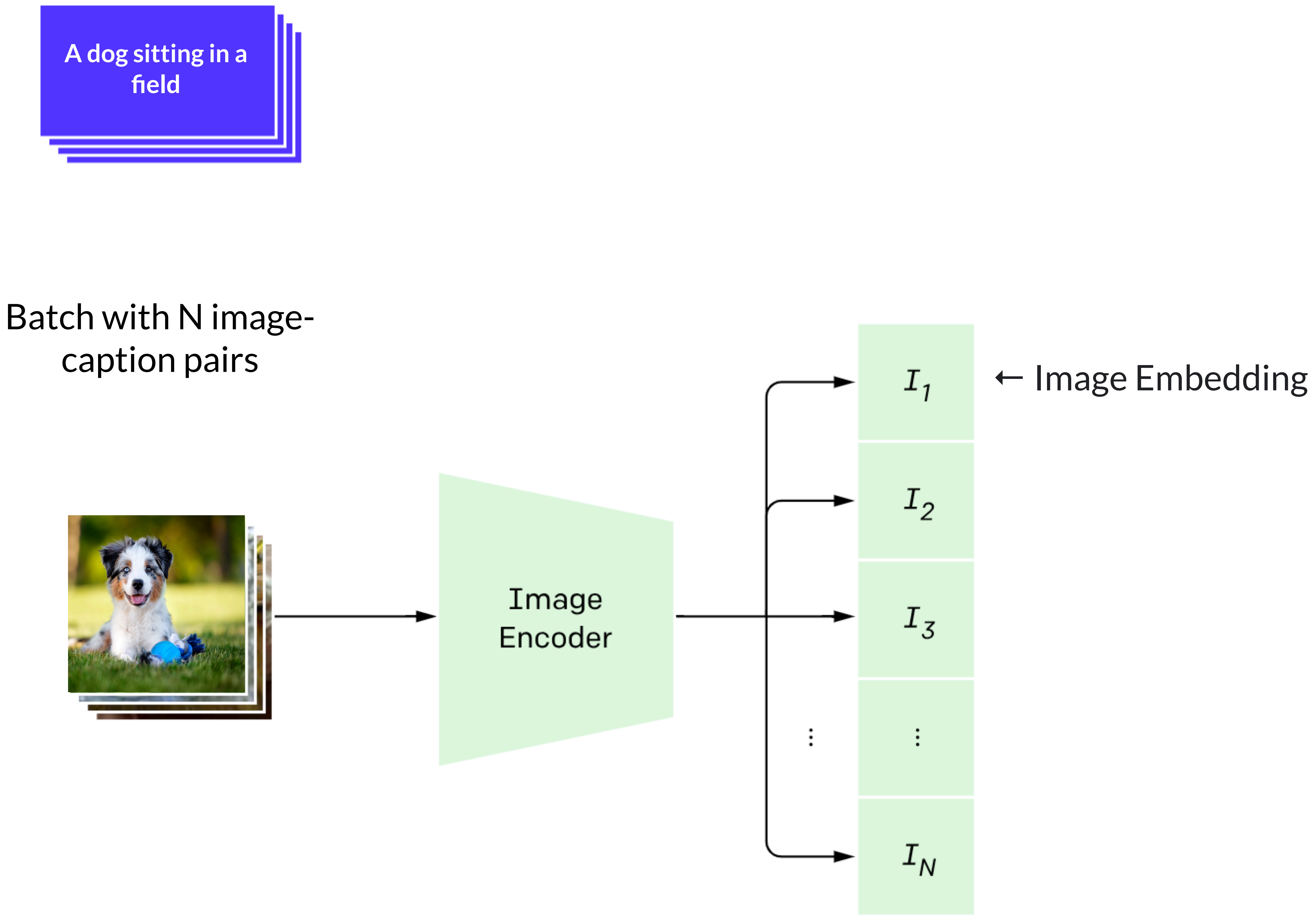

Radford et al. "Learning Transferable Visual Models From Natural Language Supervision”

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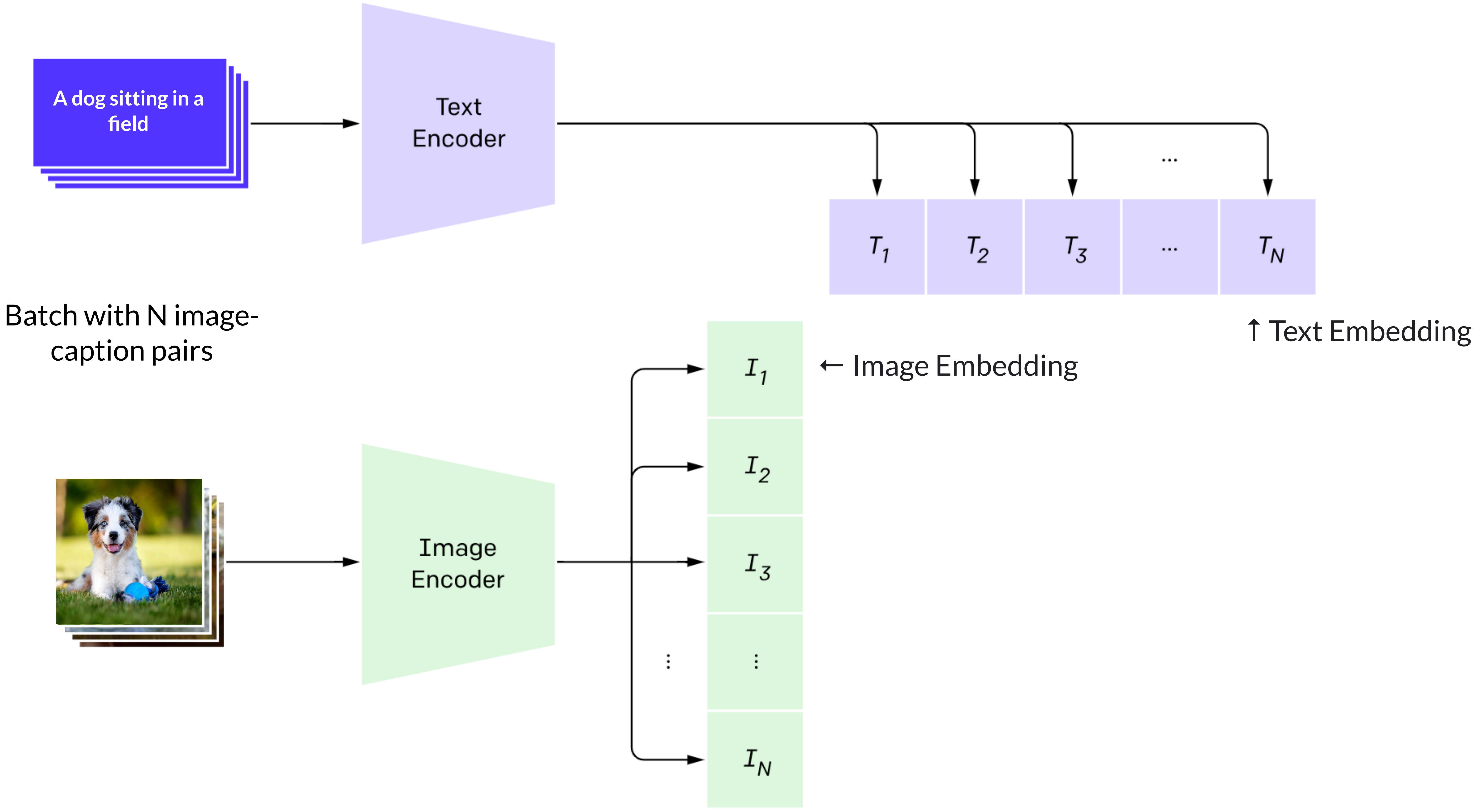

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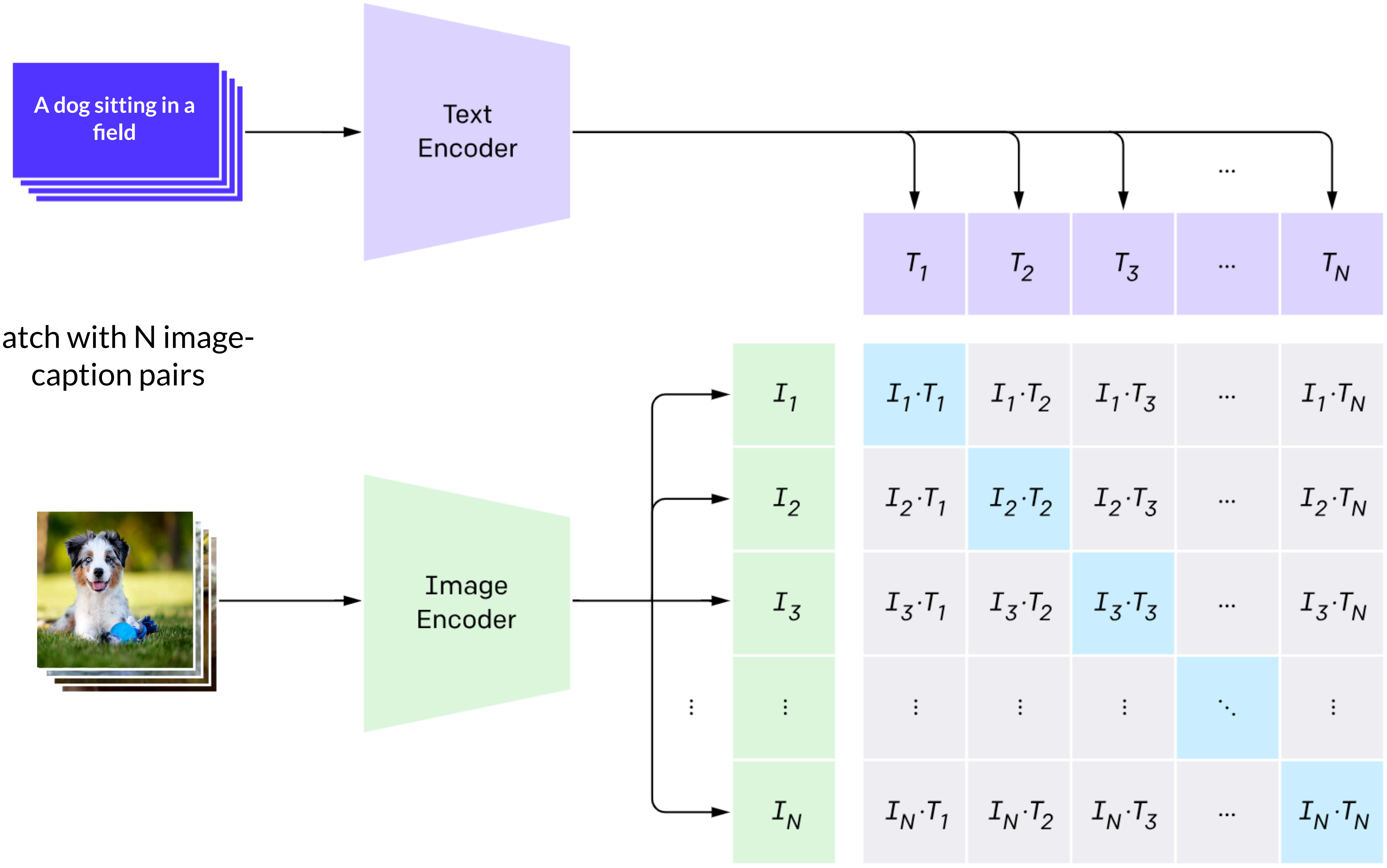


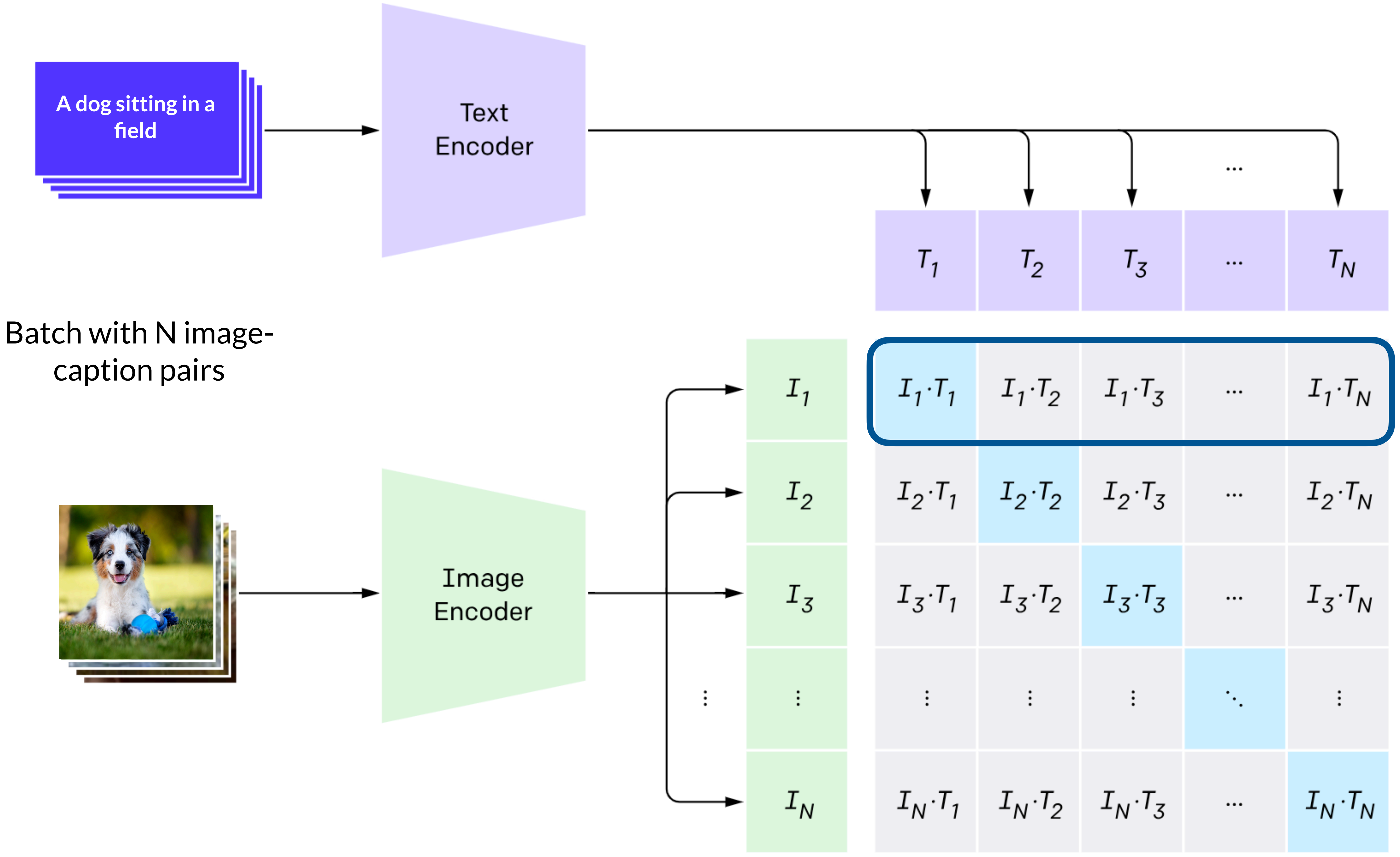
Batch with N image-caption pairs

	T_1	T_2	T_3	...	T_N
I_1	$I_1 \cdot T_1$	$I_1 \cdot T_2$	$I_1 \cdot T_3$	...	$I_1 \cdot T_N$
I_2	$I_2 \cdot T_1$	$I_2 \cdot T_2$	$I_2 \cdot T_3$	...	$I_2 \cdot T_N$
I_3	$I_3 \cdot T_1$	$I_3 \cdot T_2$	$I_3 \cdot T_3$	...	$I_3 \cdot T_N$
⋮	⋮	⋮	⋮	⋱	⋮
I_N	$I_N \cdot T_1$	$I_N \cdot T_2$	$I_N \cdot T_3$	...	$I_N \cdot T_N$

Radford et al. "Learning Transferable Visual Models From Natural Language Supervision"

Contrastive Language-Image Pretraining (CLIP)

Key Idea: Maximize the similarity between true image-text embedding pairs and minimize similarity between mismatched image-text embedding pairs



	T_1	T_2	T_3	...	T_N
I_1	$I_1 \cdot T_1$	$I_1 \cdot T_2$	$I_1 \cdot T_3$	...	$I_1 \cdot T_N$
I_2	$I_2 \cdot T_1$	$I_2 \cdot T_2$	$I_2 \cdot T_3$	...	$I_2 \cdot T_N$
I_3	$I_3 \cdot T_1$	$I_3 \cdot T_2$	$I_3 \cdot T_3$	...	$I_3 \cdot T_N$
⋮	⋮	⋮	⋮	⋱	⋮
I_N	$I_N \cdot T_1$	$I_N \cdot T_2$	$I_N \cdot T_3$	...	$I_N \cdot T_N$

Objective: InfoNCE Loss Function

$$L_{I\to T} = \sum_{k=1}^{N} -\log \frac{exp(I_k \cdot T_k/\tau)}{\sum_{j=1}^{N} exp(I_k \cdot T_j/\tau)}$$

Positive Image-Text Pairs

Negative Image-Text Pairs

Softmax Function

Radford et al. "Learning Transferable Visual Models From Natural Language Supervision"

Contrastive Language-Image Pretraining (CLIP)

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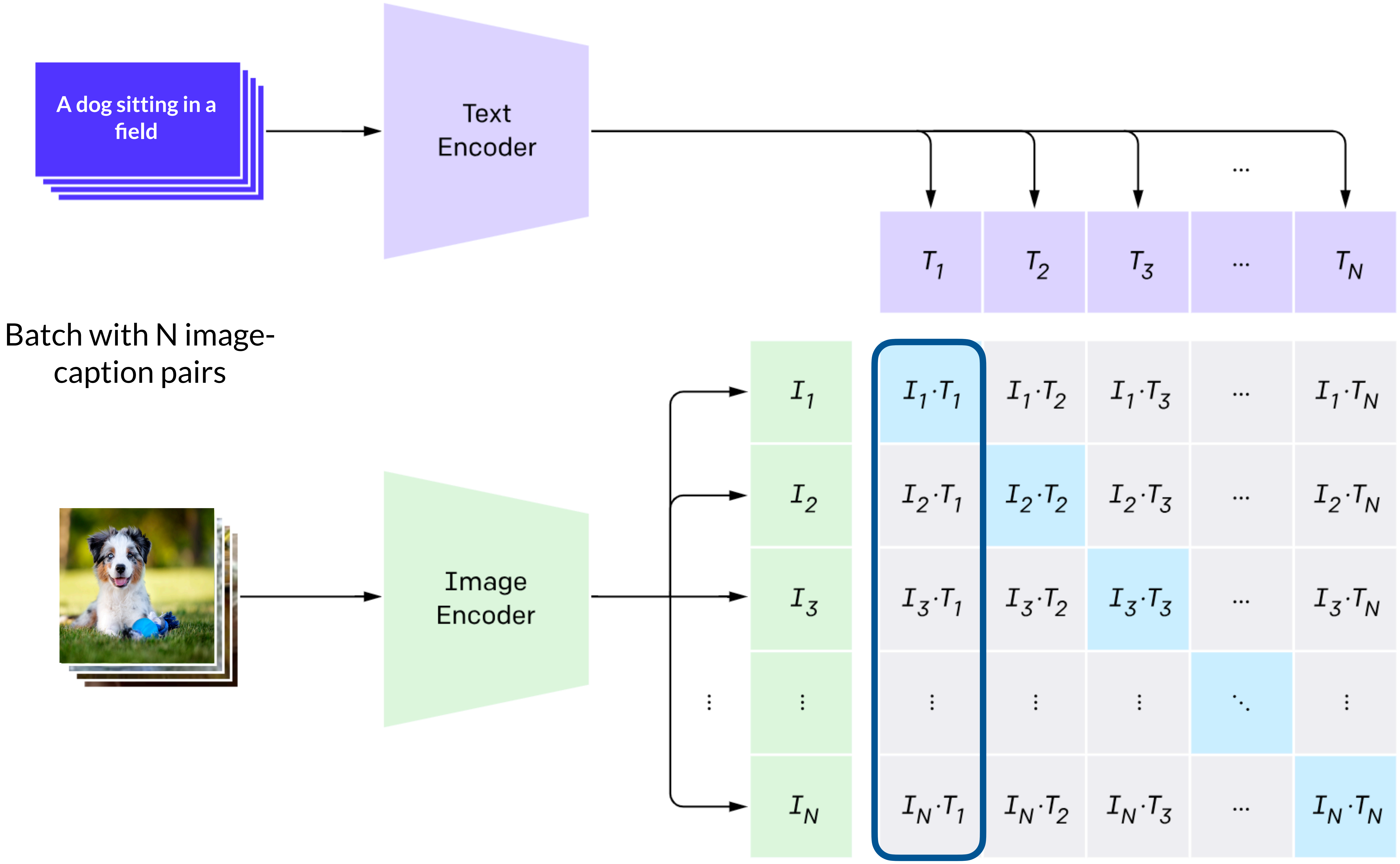

A dog sitting in a field
Text Encoder
Batch with N image-caption pairs
Image Encoder
T_1 T_2 T_3 ... T_N
I_1 I_2 I_3 ⋮ I_N
$I_1 \cdot T_1$ $I_1 \cdot T_2$ $I_1 \cdot T_3$ ... $I_1 \cdot T_N$
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Objective: InfoNCE Loss Function

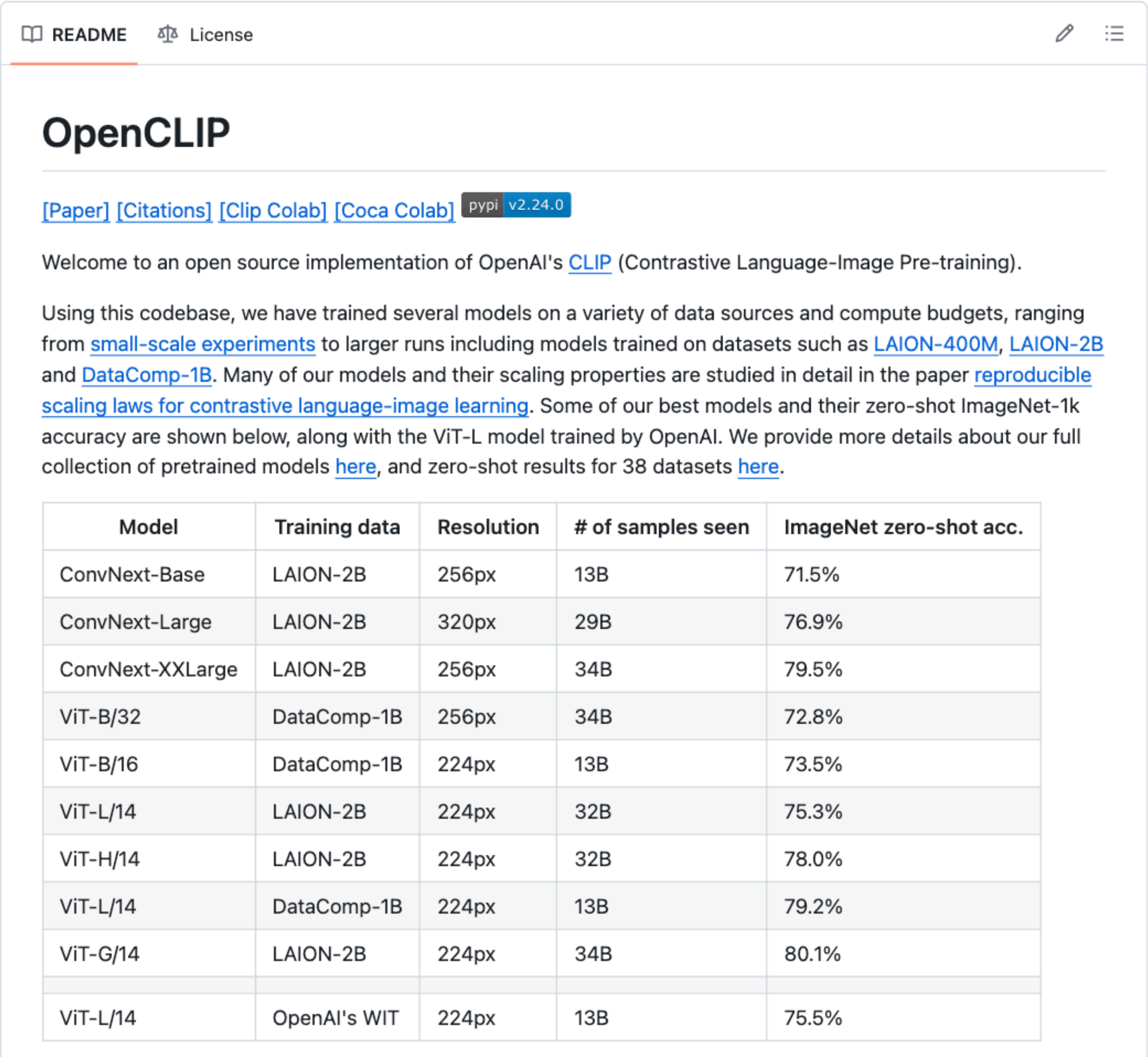
$$L_{I\to T} = \sum_{k=1}^{N} -\log \frac{exp(I_k \cdot T_k/\tau)}{\sum_{j=1}^{N} exp(I_k \cdot T_j/\tau)}$$

$$L_{T\to I} = \sum_{k=1}^{N} -\log \frac{exp(I_k \cdot T_k/\tau)}{\sum_{j=1}^{N} exp(I_j \cdot T_k/\tau)}$$

$$L = L_{T\to I} + L_{I\to T}$$

Radford et al. "Learning Transferable Visual Models From Natural Language Supervision”

OpenCLIP



OpenCLIP

[Paper] [Citations] [Clip Colab] [Coca Colab] pypi v2.24.0

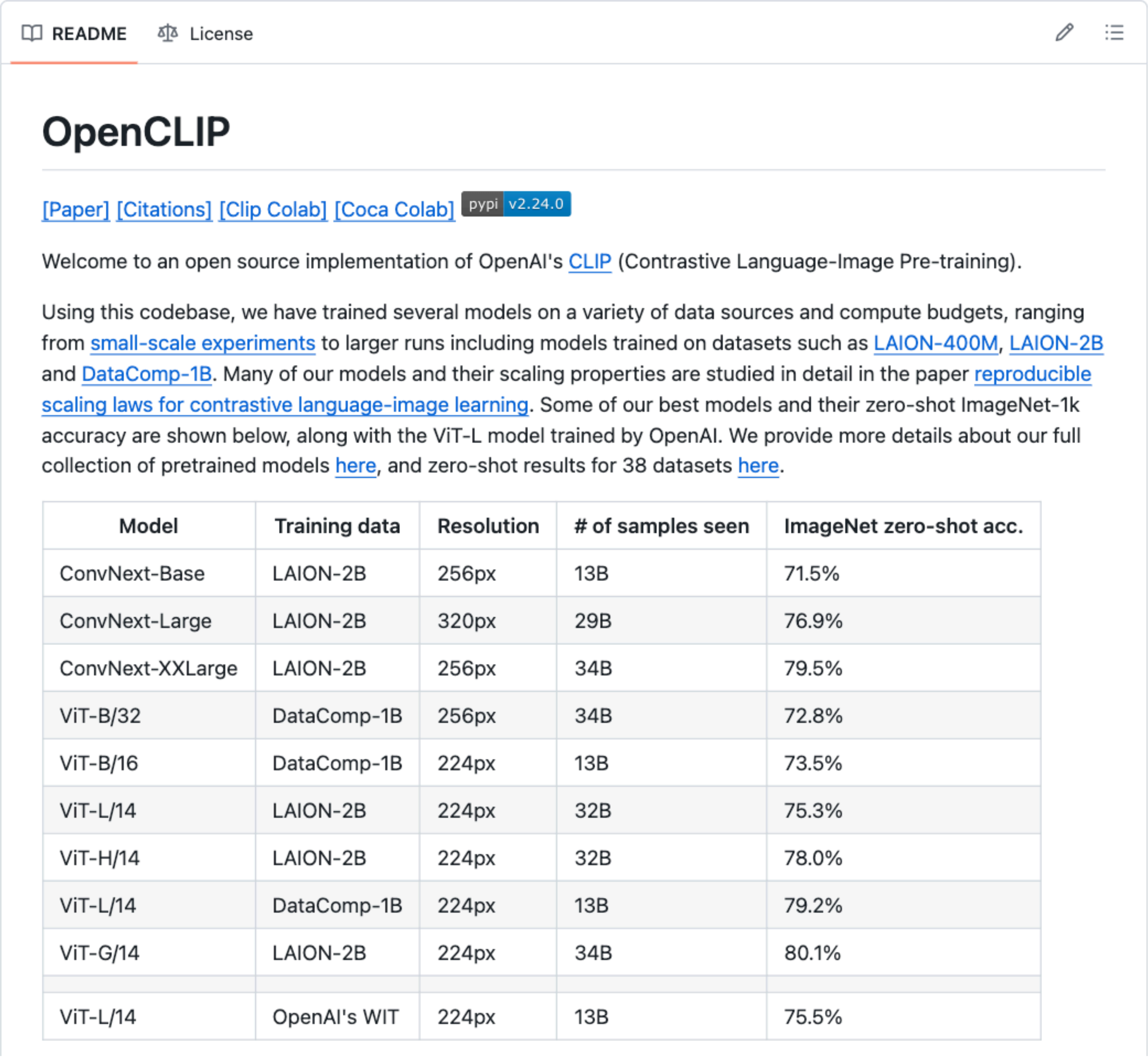
Welcome to an open source implementation of OpenAI's CLIP (Contrastive Language-Image Pre-training).

Using this codebase, we have trained several models on a variety of data sources and compute budgets, ranging from small-scale experiments to larger runs including models trained on datasets such as LAION-400M, LAION-2B and DataComp-1B. Many of our models and their scaling properties are studied in detail in the paper reproducible scaling laws for contrastive language-image learning. Some of our best models and their zero-shot ImageNet-1k accuracy are shown below, along with the ViT-L model trained by OpenAI. We provide more details about our full collection of pretrained models here, and zero-shot results for 38 datasets here.

Model	Training data	Resolution	# of samples seen	ImageNet zero-shot acc.
ConvNext-Base	LAION-2B	256px	13B	71.5%
ConvNext-Large	LAION-2B	320px	29B	76.9%
ConvNext-XXLarge	LAION-2B	256px	34B	79.5%
ViT-B/32	DataComp-1B	256px	34B	72.8%
ViT-B/16	DataComp-1B	224px	13B	73.5%
ViT-L/14	LAION-2B	224px	32B	75.3%
ViT-H/14	LAION-2B	224px	32B	78.0%
ViT-L/14	DataComp-1B	224px	13B	79.2%
ViT-G/14	LAION-2B	224px	34B	80.1%
ViT-L/14	OpenAI's WIT	224px	13B	75.5%

Ilharco et al. “OpenCLIP”
Cherti et al. “Reproducible scaling laws for contrastive language-image learning”

OpenCLIP



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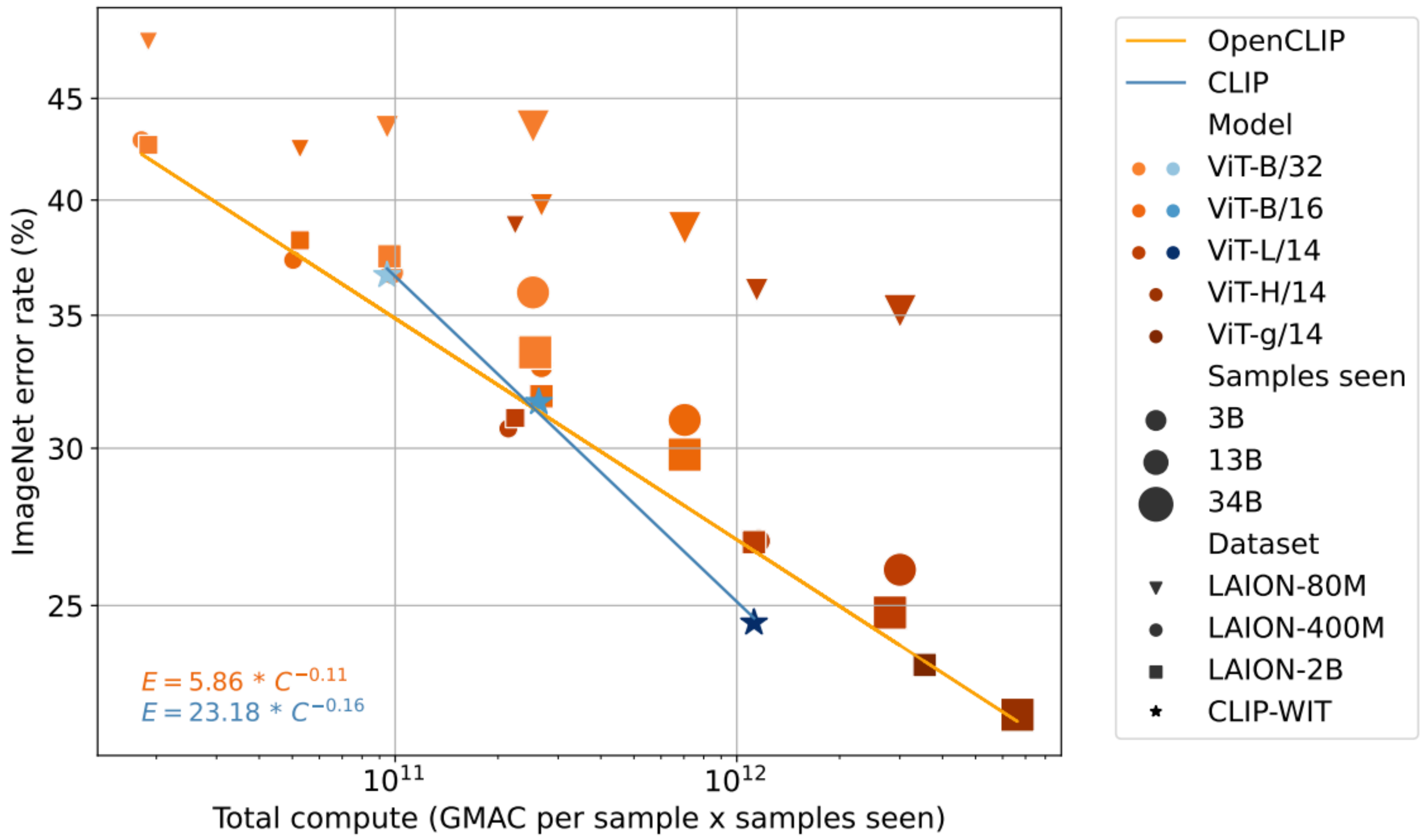


Ilharco et al. "OpenCLIP"
Cherti et al. "Reproducible scaling laws for contrastive language-image learning"

ConVIRT

Key Idea: Maximize the similarity between true image-text embedding pairs and minimize similarity between mismatched image-text embedding pairs

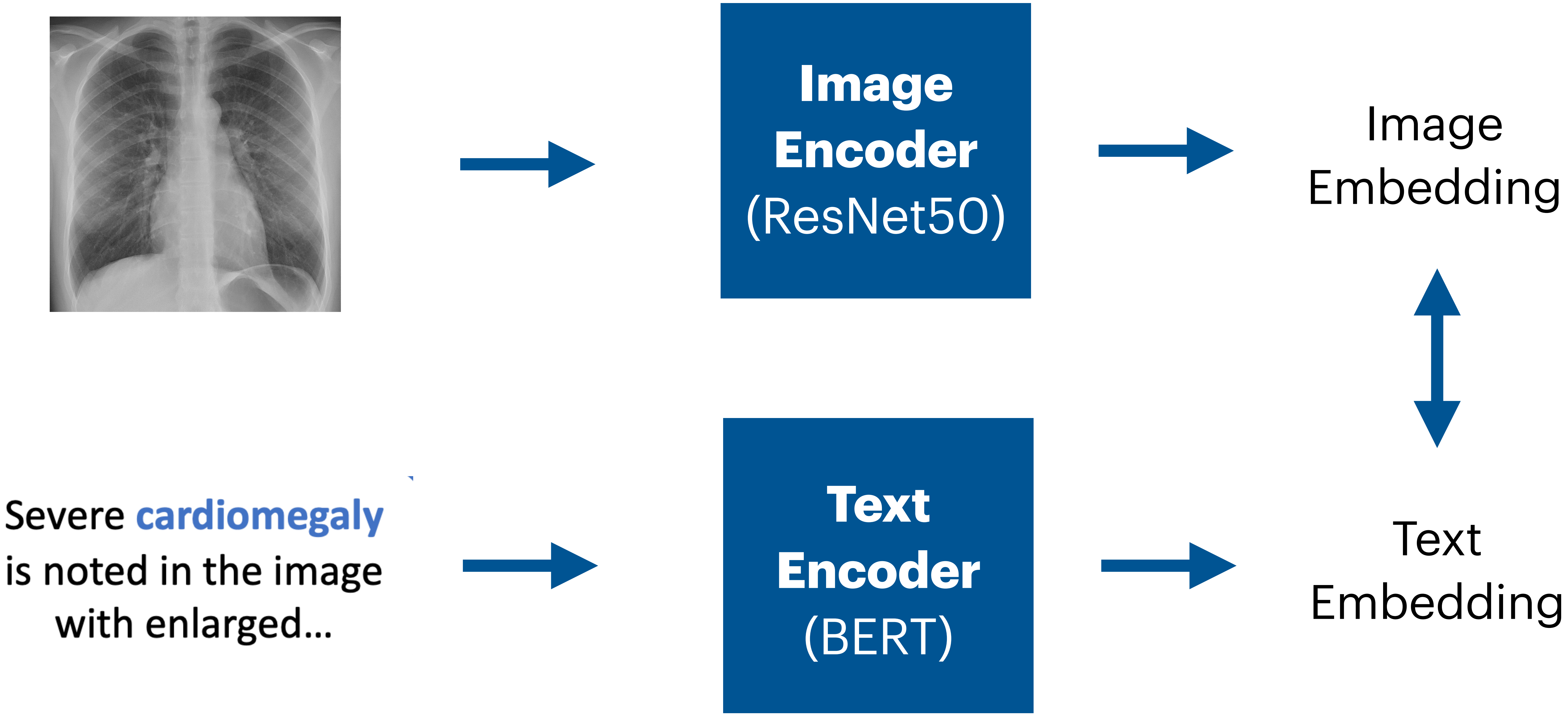


Image Encoder (ResNet50)

Image Embedding

Severe **cardiomegaly** is noted in the image with enlarged…

Text Encoder (BERT)

Text Embedding

Zhang et al. "Contrastive Learning of Medical Visual Representations from Paired Images and Text”

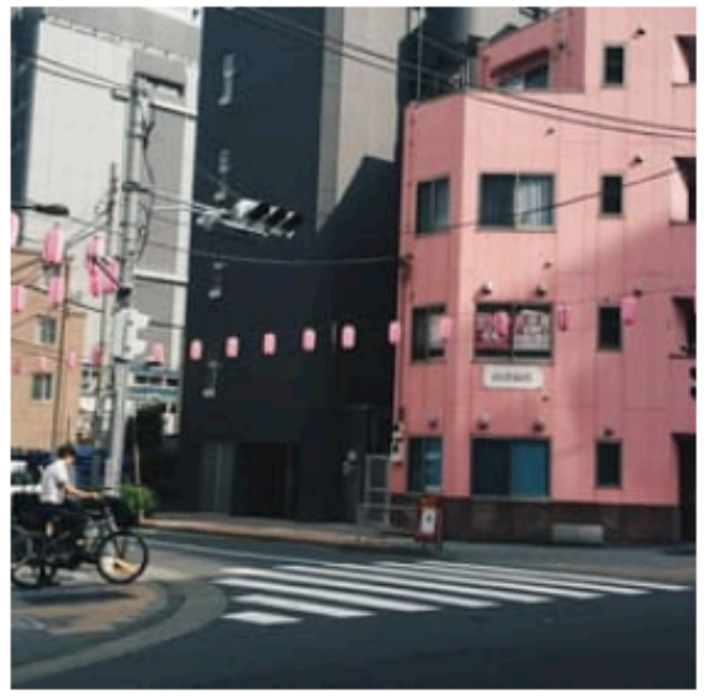
General-Domain Data: LAION-5B

LAION-5B contains 5 billion image-text pairs obtained from CommonCrawl

C: Green Apple Chair

C: sun snow dog

C: Color Palettes

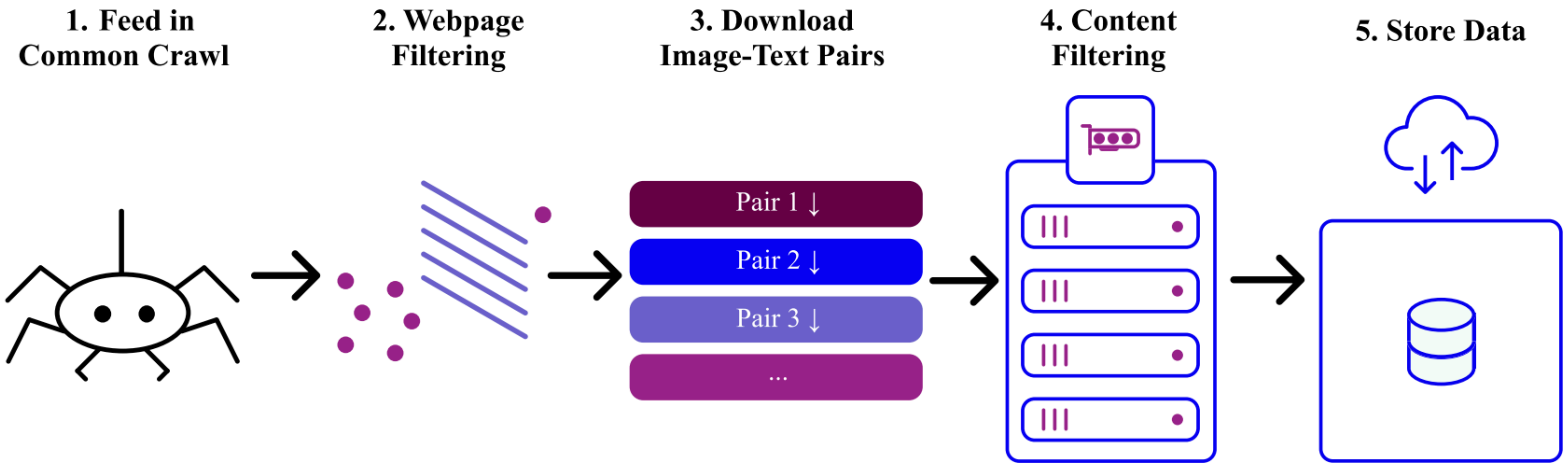


C: pink, japan, aesthetic image

Schumann et al. “LAION-5B: An open large-scale dataset for training next generation image-text models”

General-Domain Data: LAION-5B

LAION-5B contains 5 billion image-text pairs obtained from CommonCrawl



Schumann et al. “LAION-5B: An open large-scale dataset for training next generation image-text models”

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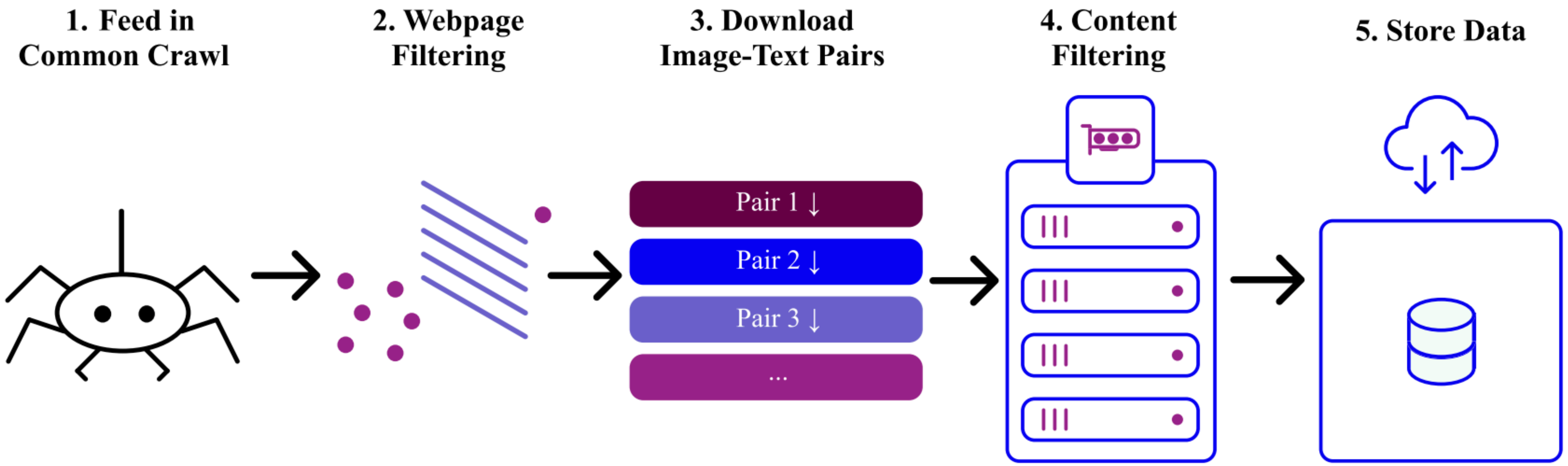


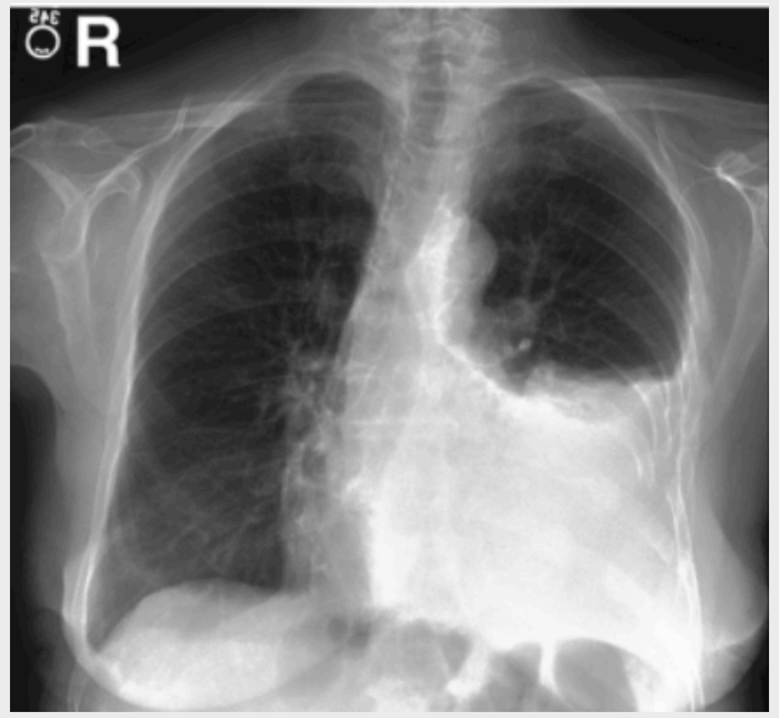
Content filtering is performed using a pre-trained CLIP model
(i.e. by computing cosine similarity between the image and text embeddings)

Schumann et al. "LAION-5B: An open large-scale dataset for training next generation image-text models"

Medical-Domain Data

MIMIC-CXR

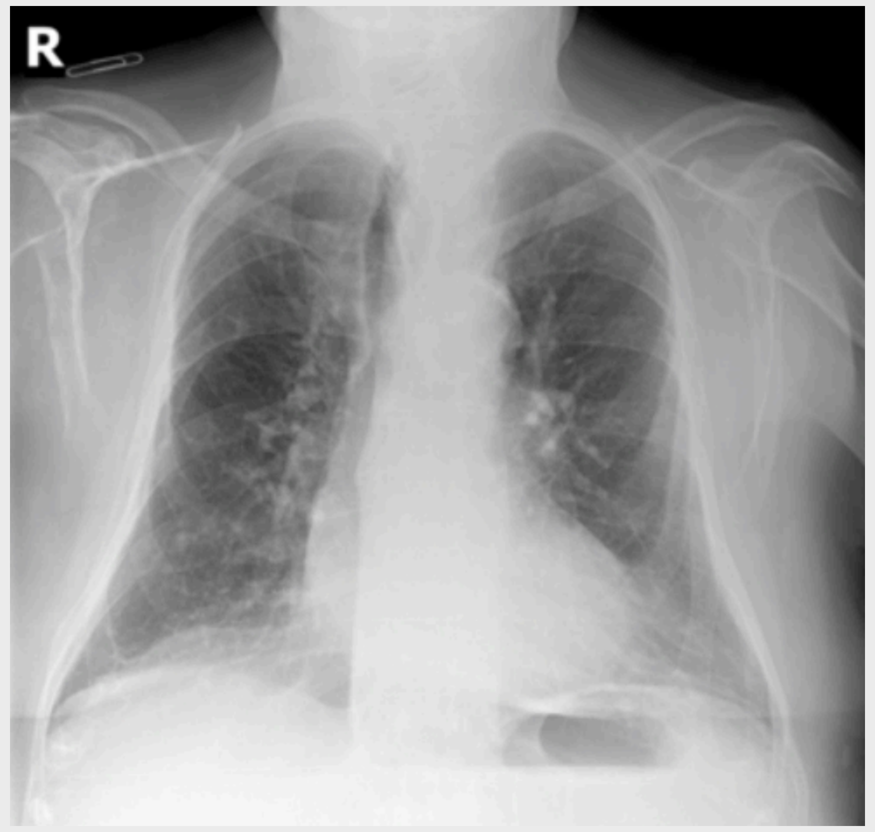
370k chest X-rays with 220k reports



Cardiac size cannot be evaluated. Large left pleural effusion is new. Small right effusion is new. The upper lungs are clear. There is no pneumothorax.

PadChest

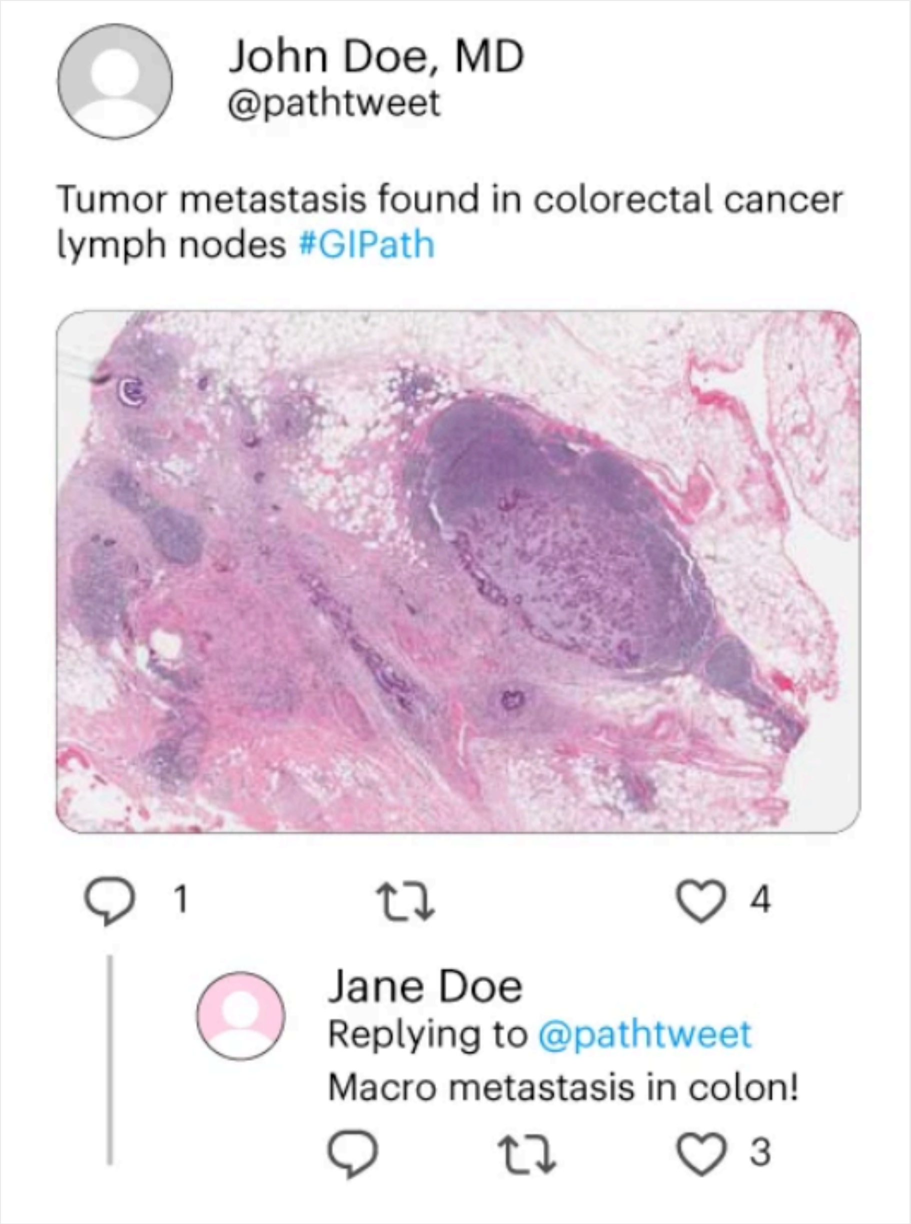
160k chest X-rays with 110k reports (Spanish)



cambi pulmonar cronic sever. sign fibrosis bibasal. sutil infiltr pseudonodul milimetr vidri deslustr localiz bas. cifosis sever

OpenPath

200k histopathology image-text pairs (Twitter)



John Doe, MD
@pathtweet

Tumor metastasis found in colorectal cancer lymph nodes #GIPath

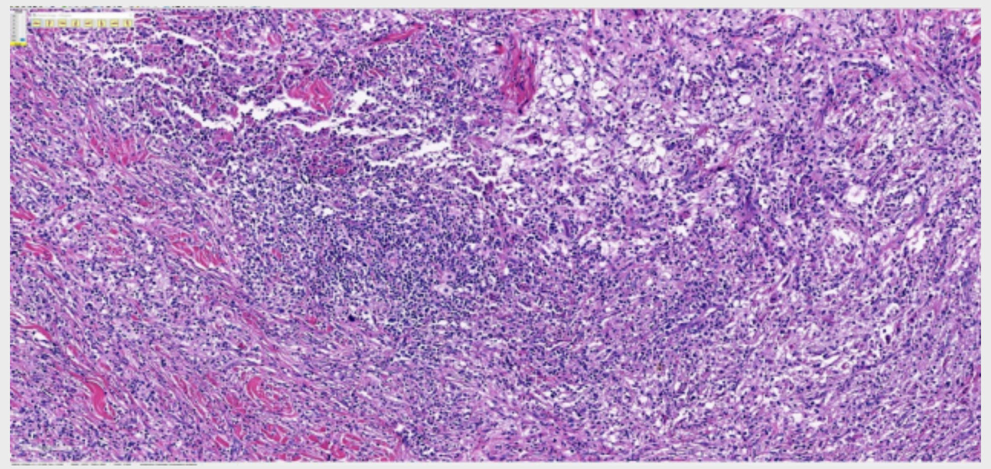
1 4

Jane Doe
Replying to @pathtweet
Macro metastasis in colon!

3

Quilt-1M

1M histopathology image-text pairs (Youtube)



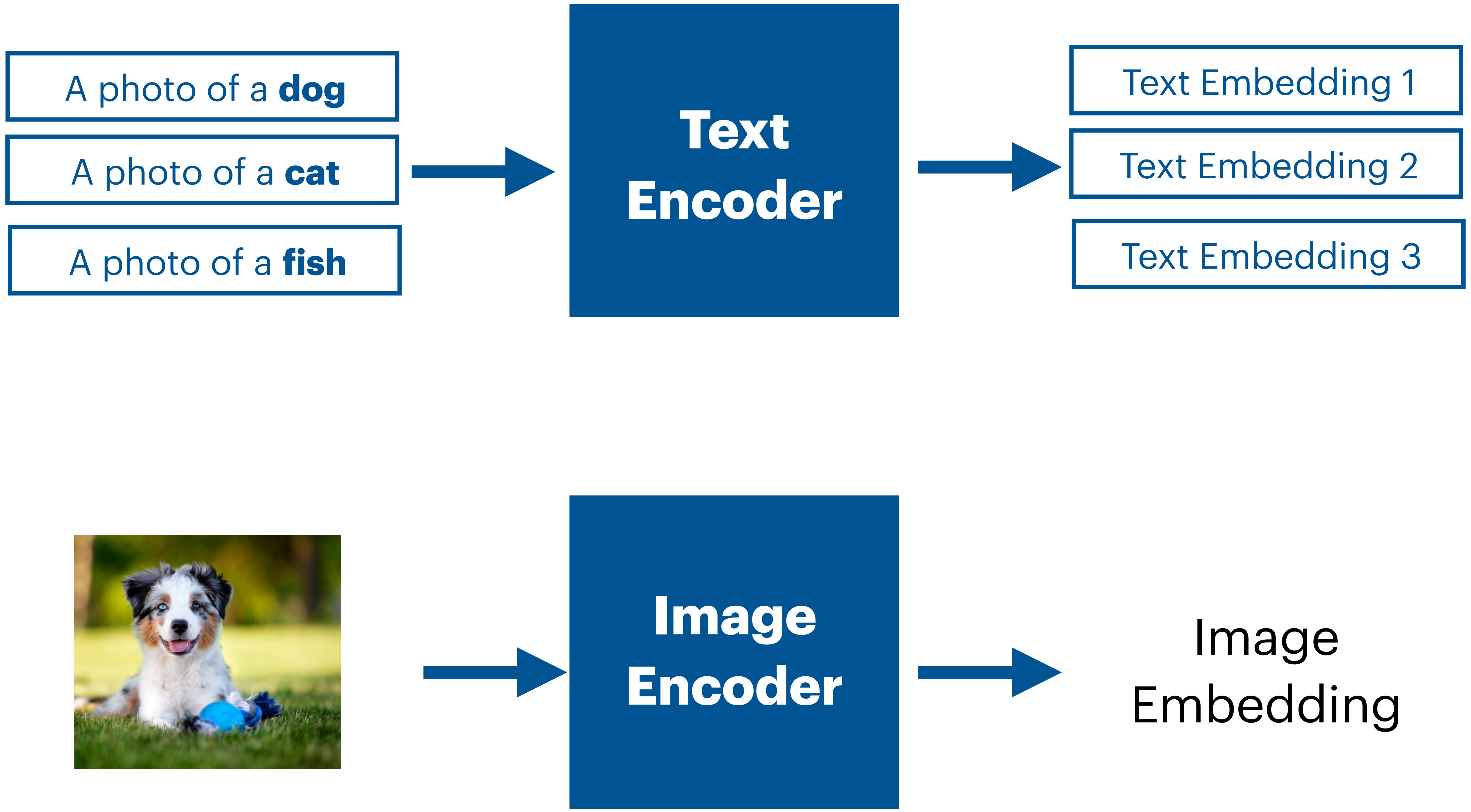
Large histiocytes with abundant cytoplasm identified as Rosai-Dorfman histiocytes

Johnson et al. "MIMIC-CXR, a de-identified publicly available database of chest radiographs with free-text reports."
Bustos et al. "PadChest: A large chest x-ray image dataset with multi-label annotated reports"
Ikezogwo et al. "Quilt-1M: One Million Image-Text Pairs for Histopathology"
Huang et al. "A visual-language foundation model for pathology image analysis using medical Twitter"

Part 2: Evaluating VLMs

Evaluating VLMs

Zero-Shot Classification



A photo of a **dog**

A photo of a **cat**

A photo of a **fish**

Text Encoder

Text Embedding 1

Text Embedding 2

Text Embedding 3

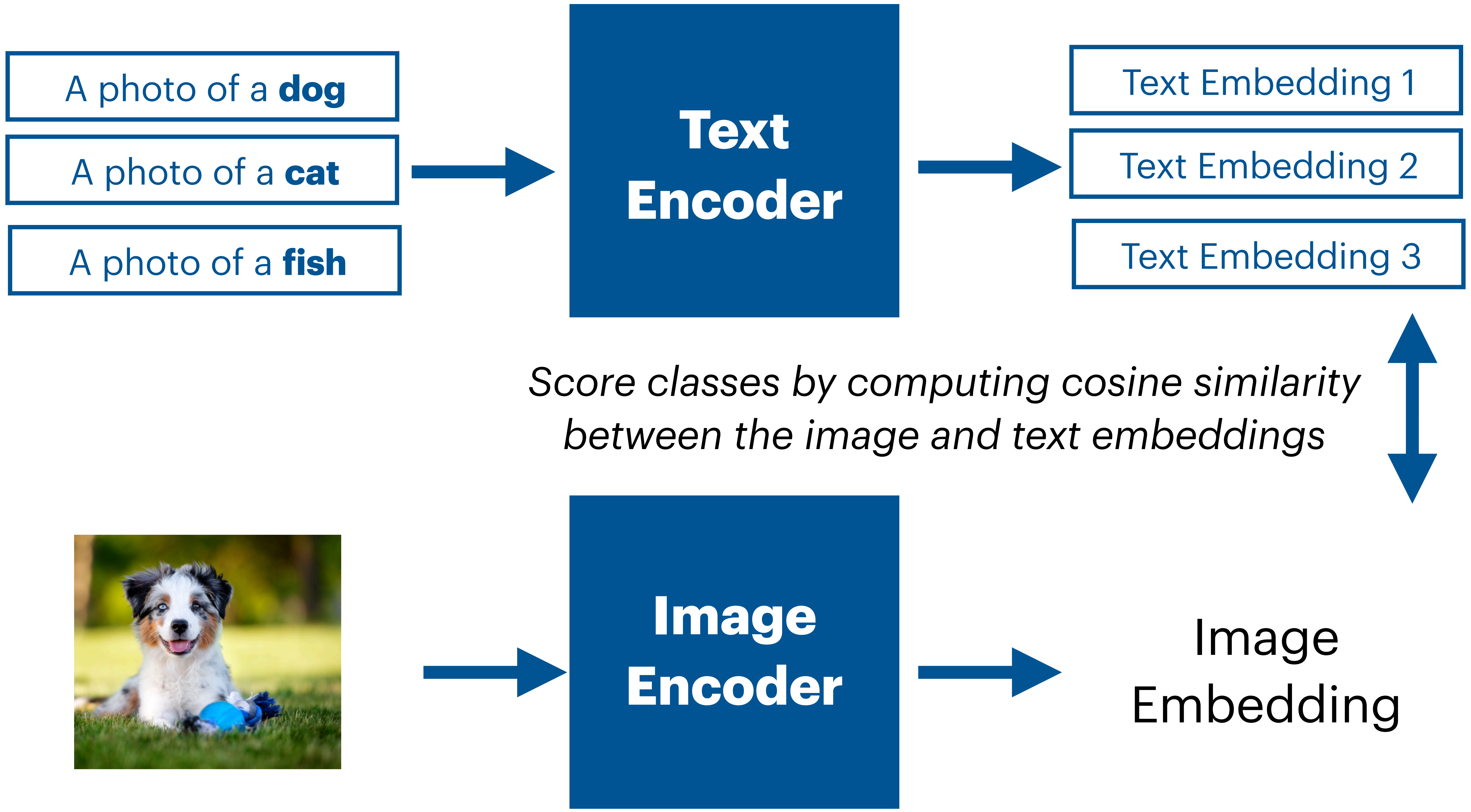
Image Encoder

Image Embedding

Radford et al. "Learning Transferable Visual Models From Natural Language Supervision"

Evaluating VLMs

Zero-Shot Classification



A photo of a **dog**

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Text Encoder

Text Embedding 1

Text Embedding 2

Text Embedding 3

Score classes by computing cosine similarity between the image and text embeddings

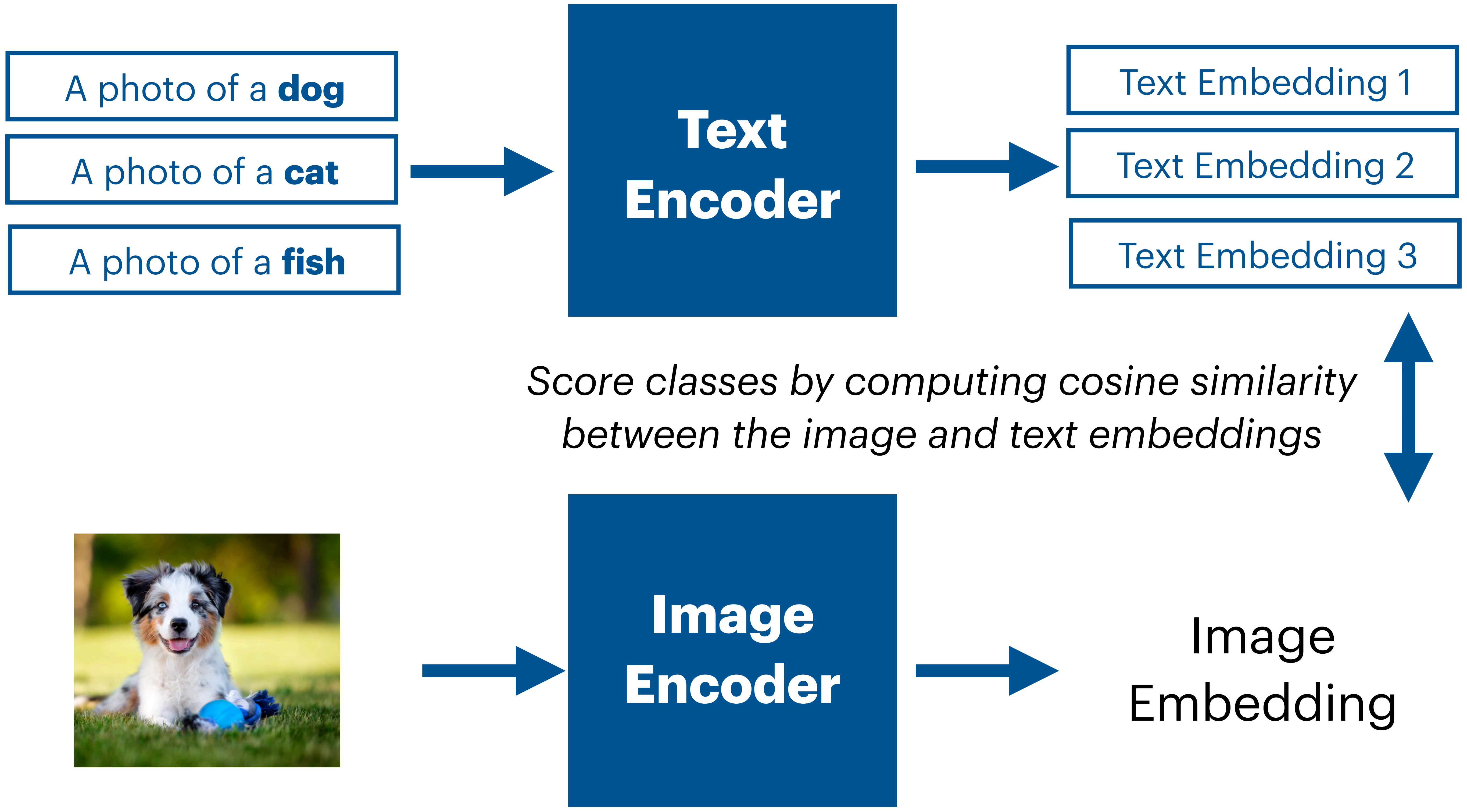
Image Encoder

Image Embedding

Radford et al. "Learning Transferable Visual Models From Natural Language Supervision”

Evaluating VLMs

Zero-Shot Classification



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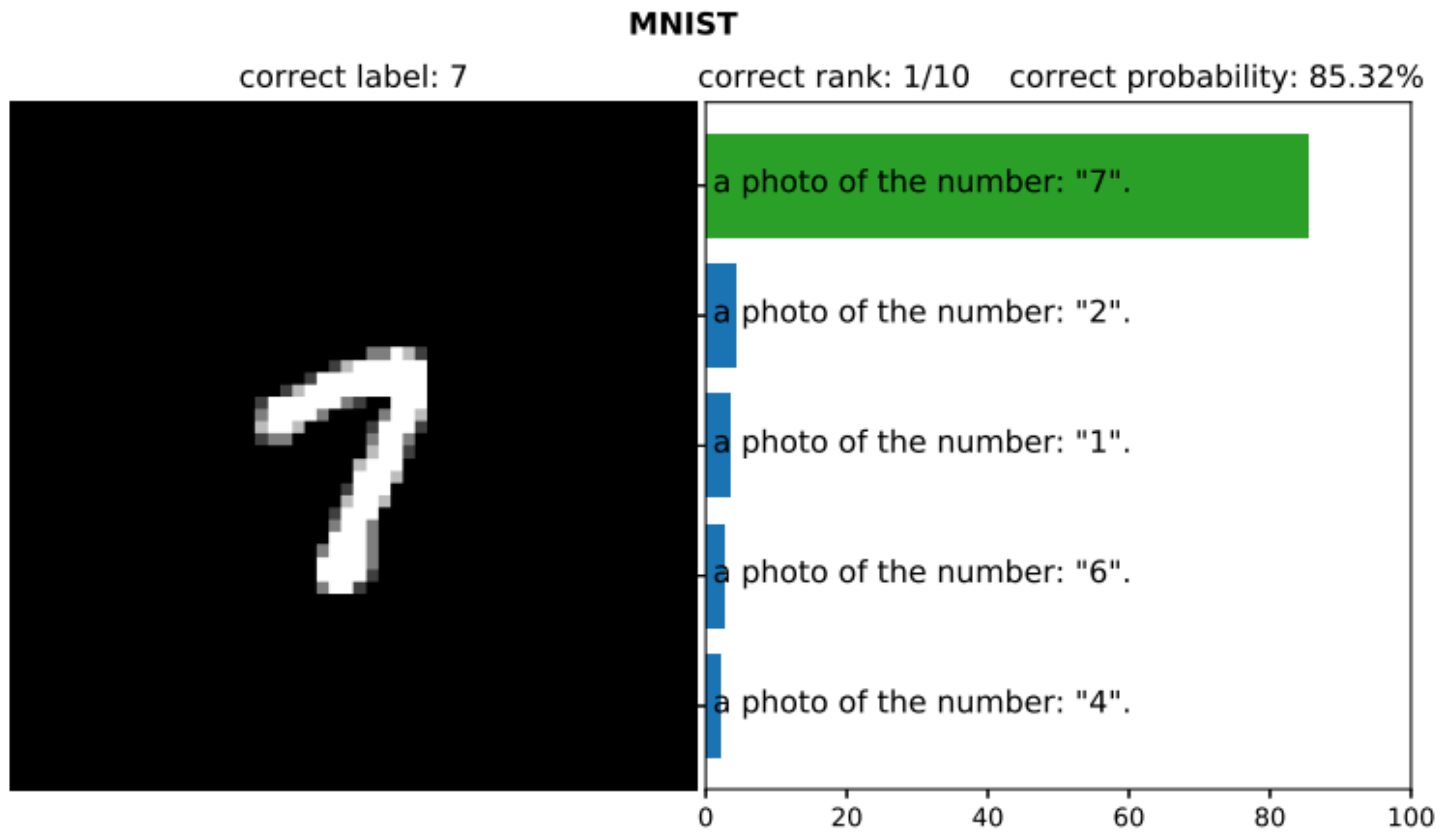
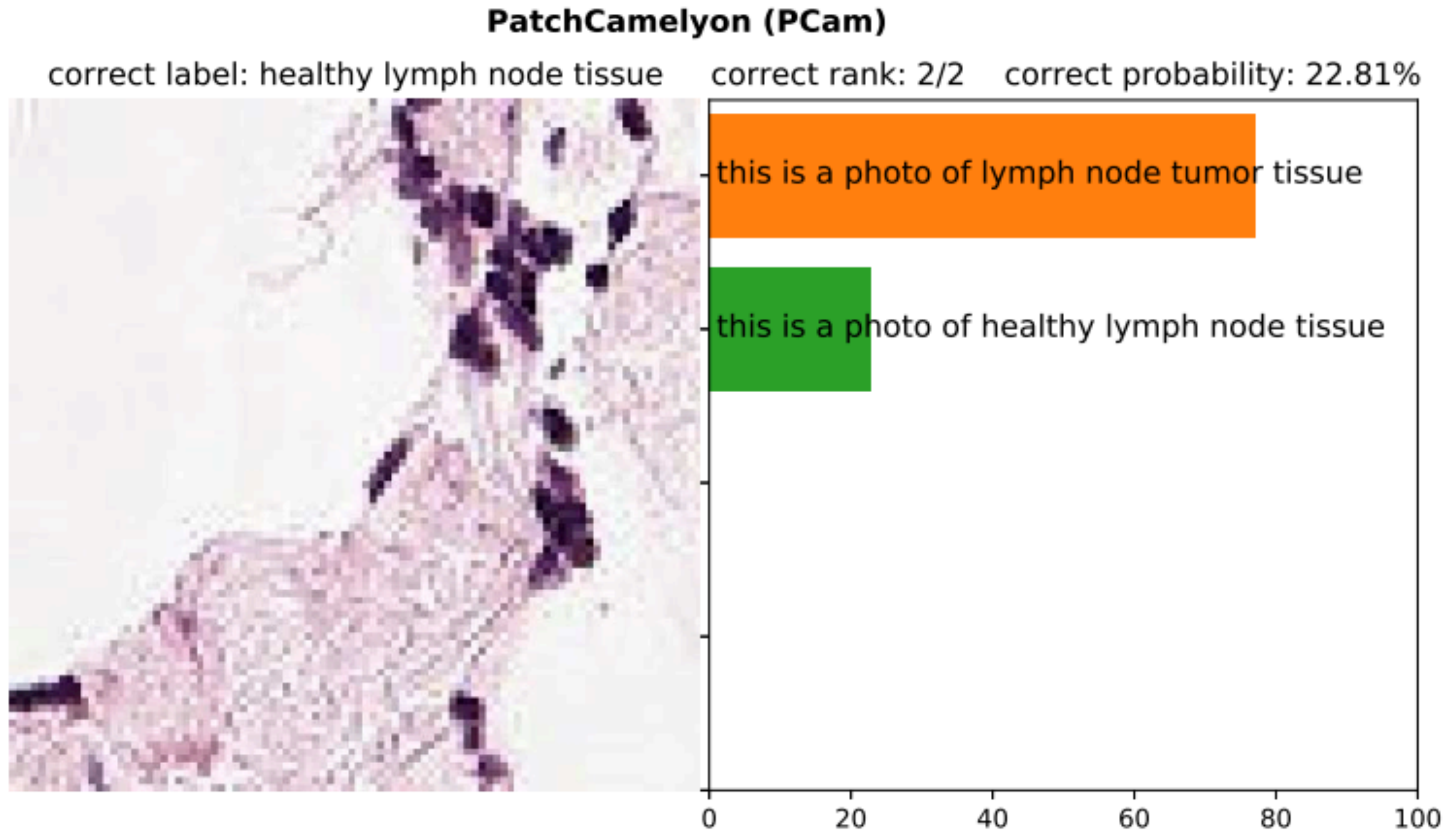
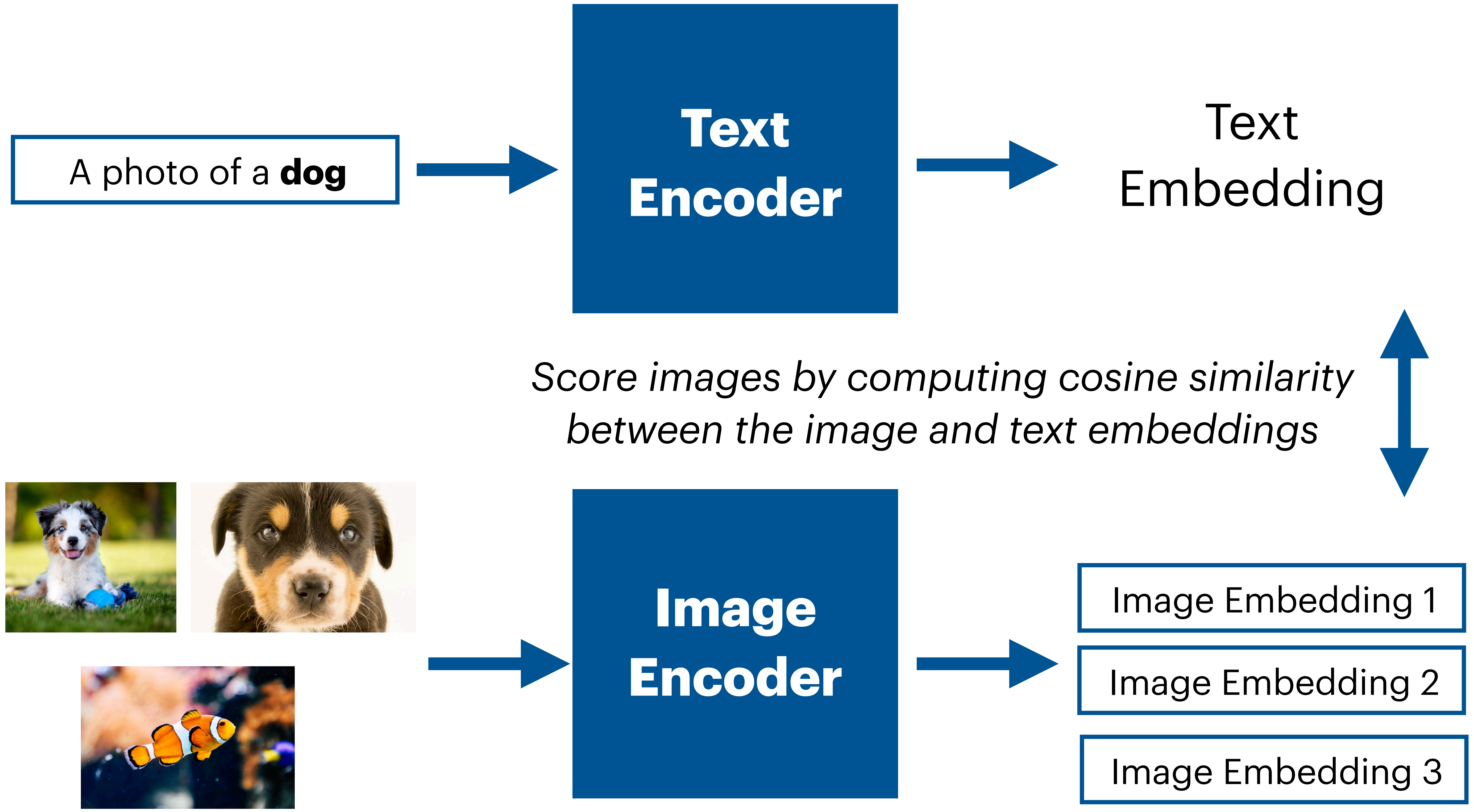




Radford et al. "Learning Transferable Visual Models From Natural Language Supervision"

Evaluating VLMs

Text → Image Retrieval



A photo of a **dog**

Text Encoder

Text Embedding

Score images by computing cosine similarity between the image and text embeddings

Image Encoder

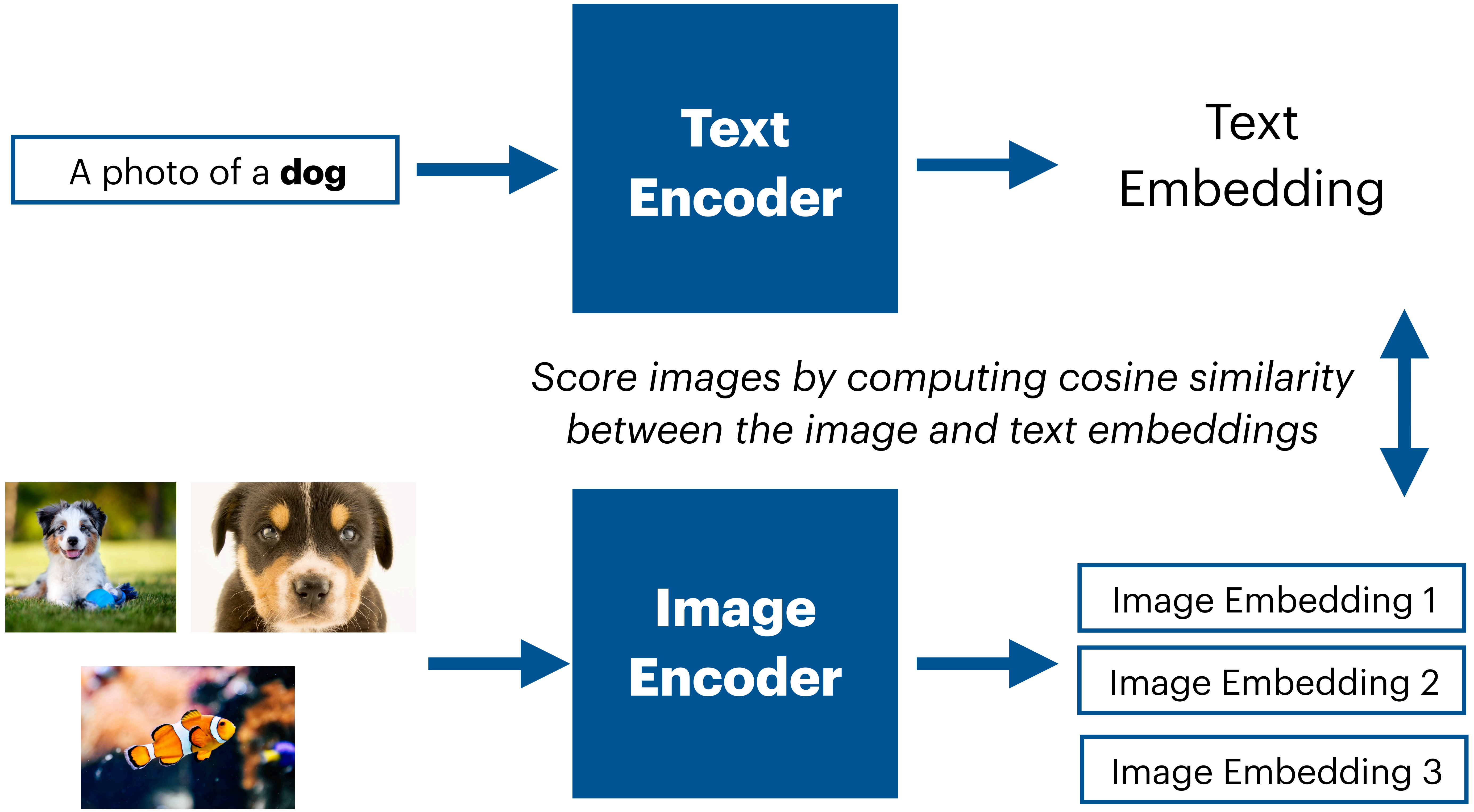
Image Embedding 1

Image Embedding 2

Image Embedding 3

Evaluating VLMs

Text → Image Retrieval



A photo of a **dog**

Text Encoder

Text Embedding

Score images by computing cosine similarity between the image and text embeddings

Image Encoder

Image Embedding 1

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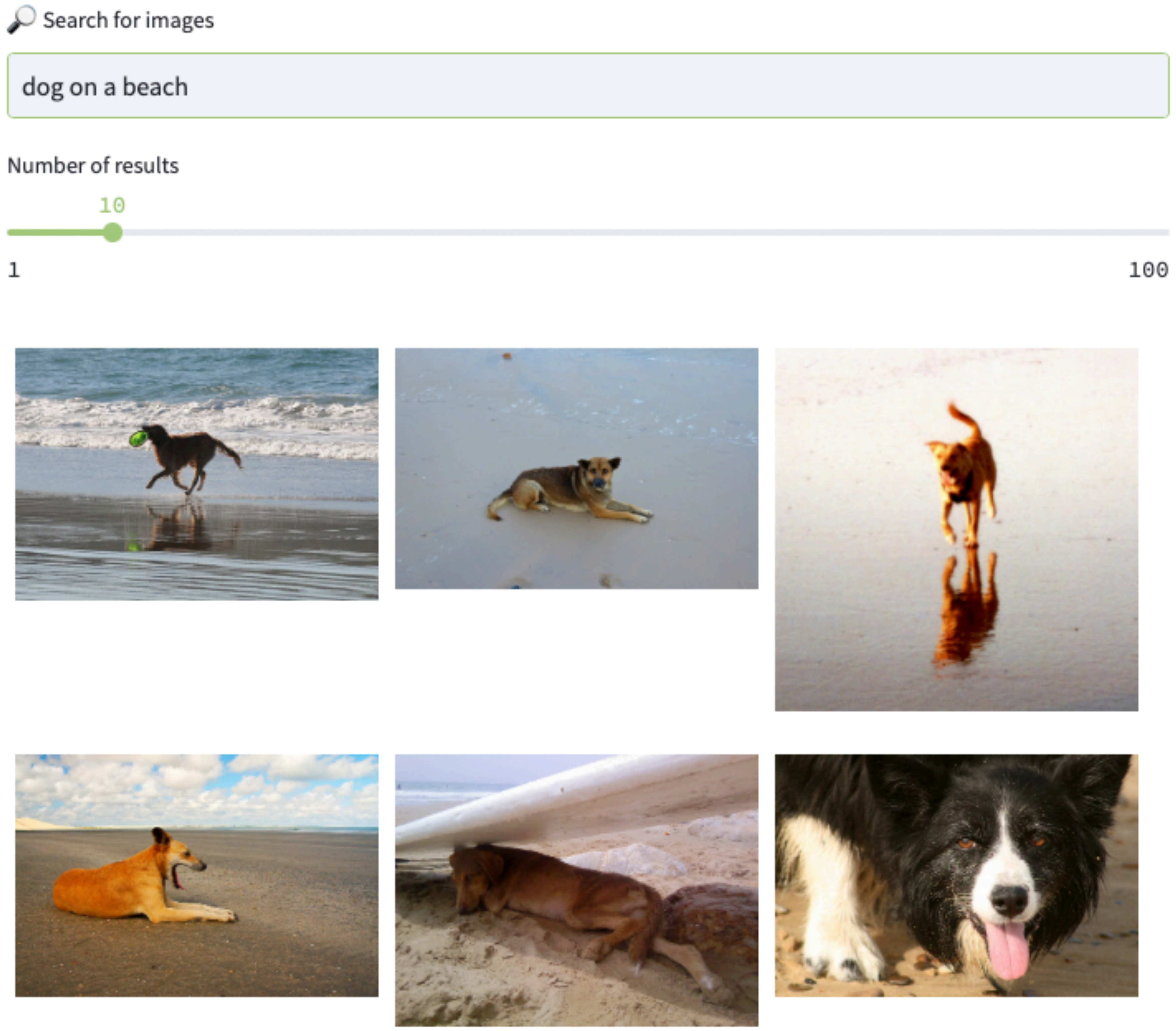
Image Embedding 3



Search for images

dog on a beach

Number of results

10

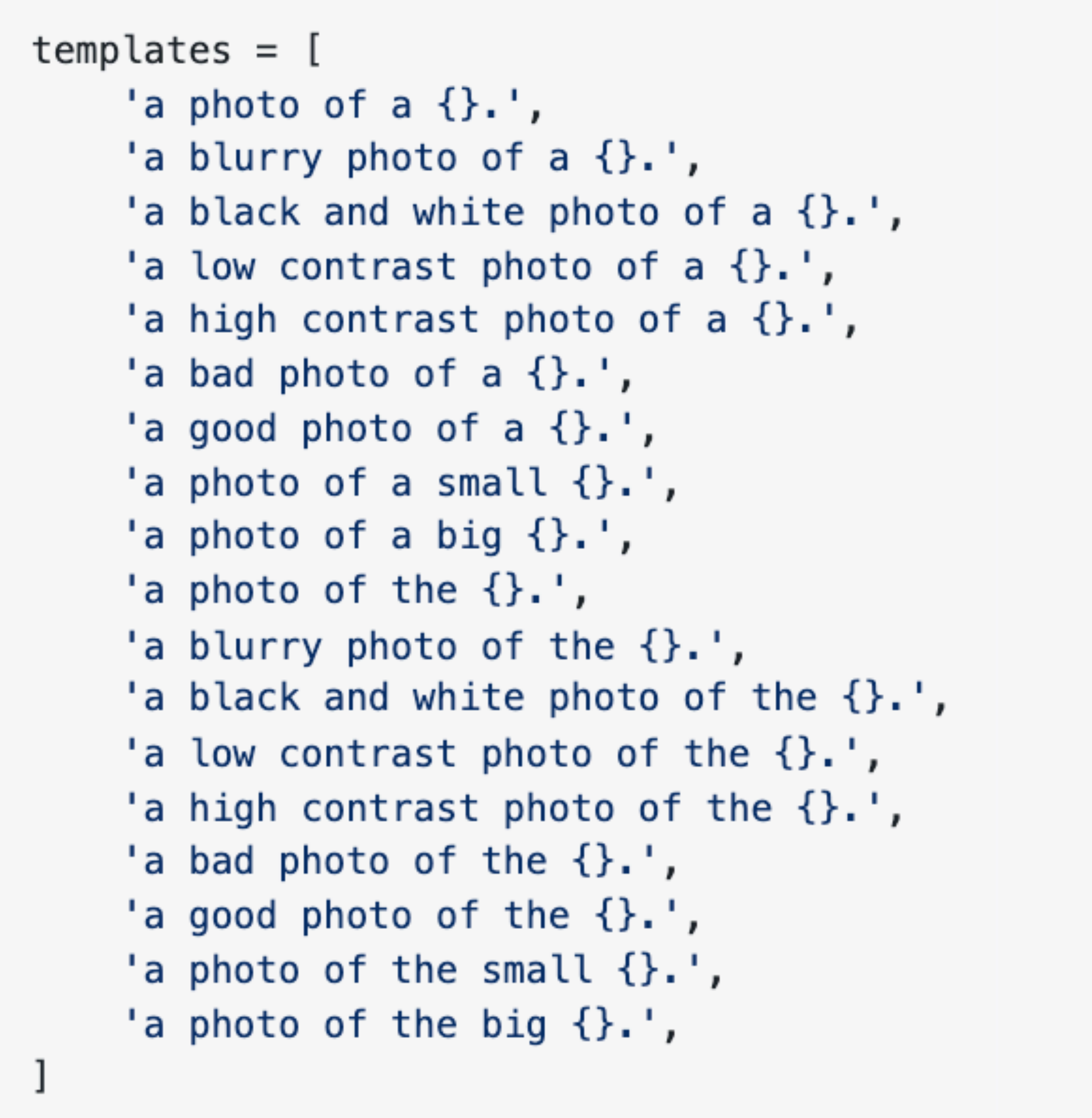
1

100

Prompting VLMs

Textual Prompts

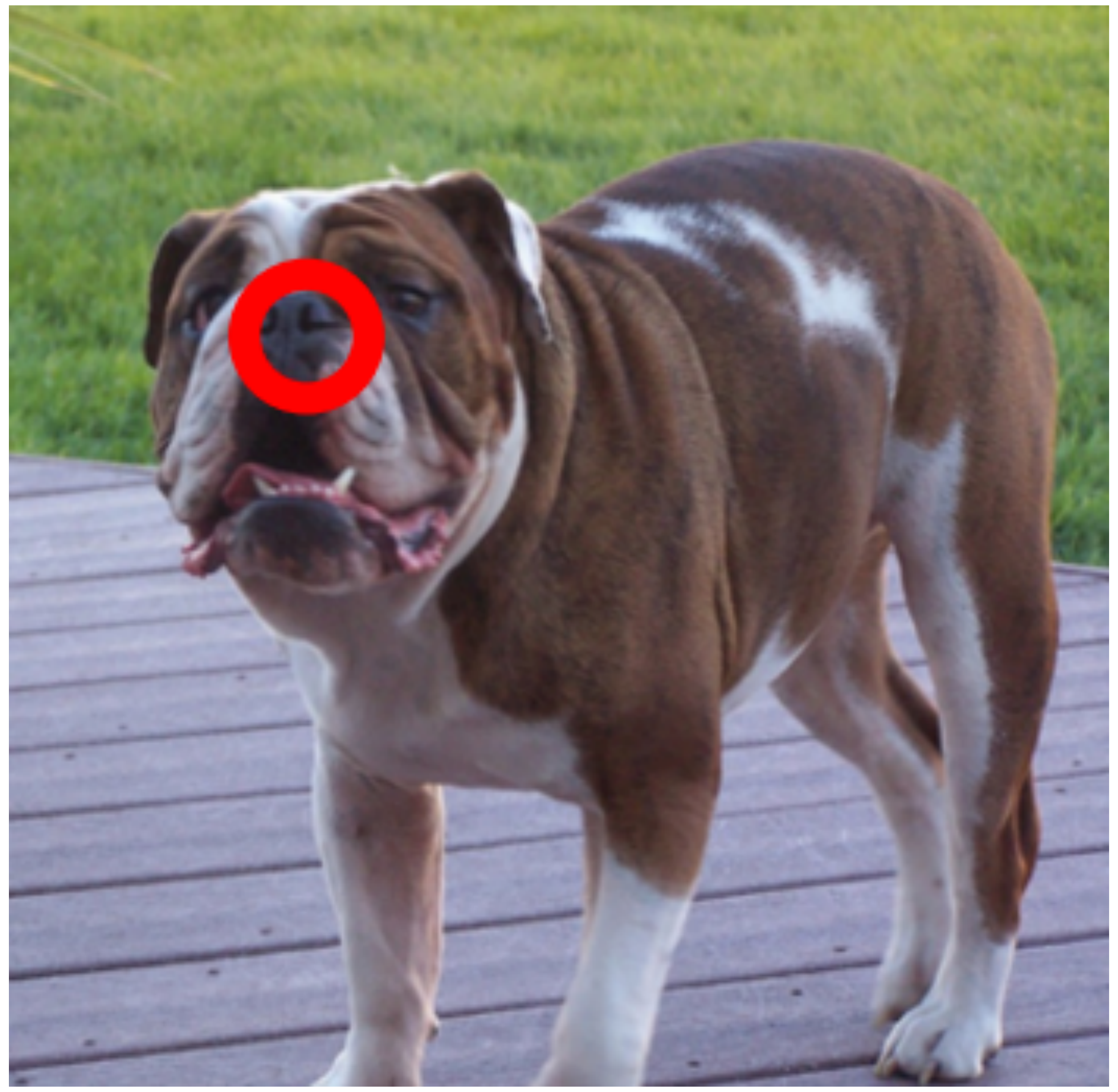
Example text prompts used by CLIP for zero-shot classification on CIFAR-10



```
templates = [
    'a photo of a {}.',
    'a blurry photo of a {}.',
    'a black and white photo of a {}.',
    'a low contrast photo of a {}.',
    'a high contrast photo of a {}.',
    'a bad photo of a {}.',
    'a good photo of a {}.',
    'a photo of a small {}.',
    'a photo of a big {}.',
    'a photo of the {}.',
    'a blurry photo of the {}.',
    'a black and white photo of the {}.',
    'a low contrast photo of the {}.',
    'a high contrast photo of the {}.',
    'a bad photo of the {}.',
    'a good photo of the {}.',
    'a photo of the small {}.',
    'a photo of the big {}.',
]
```

Visual Prompts

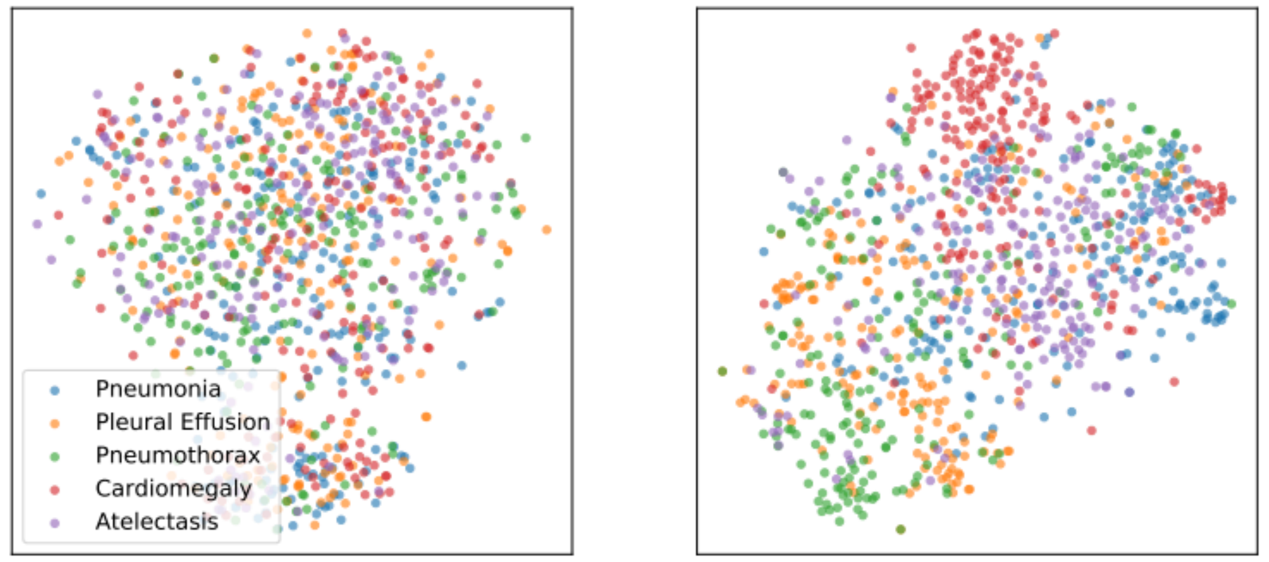
Adding visual signal to images can help with targeted retrieval and classification



Radford et al. "Learning Transferable Visual Models From Natural Language Supervision"
Shtedritski et al. “What does CLIP know about a red circle? Visual prompt engineering for VLMs”

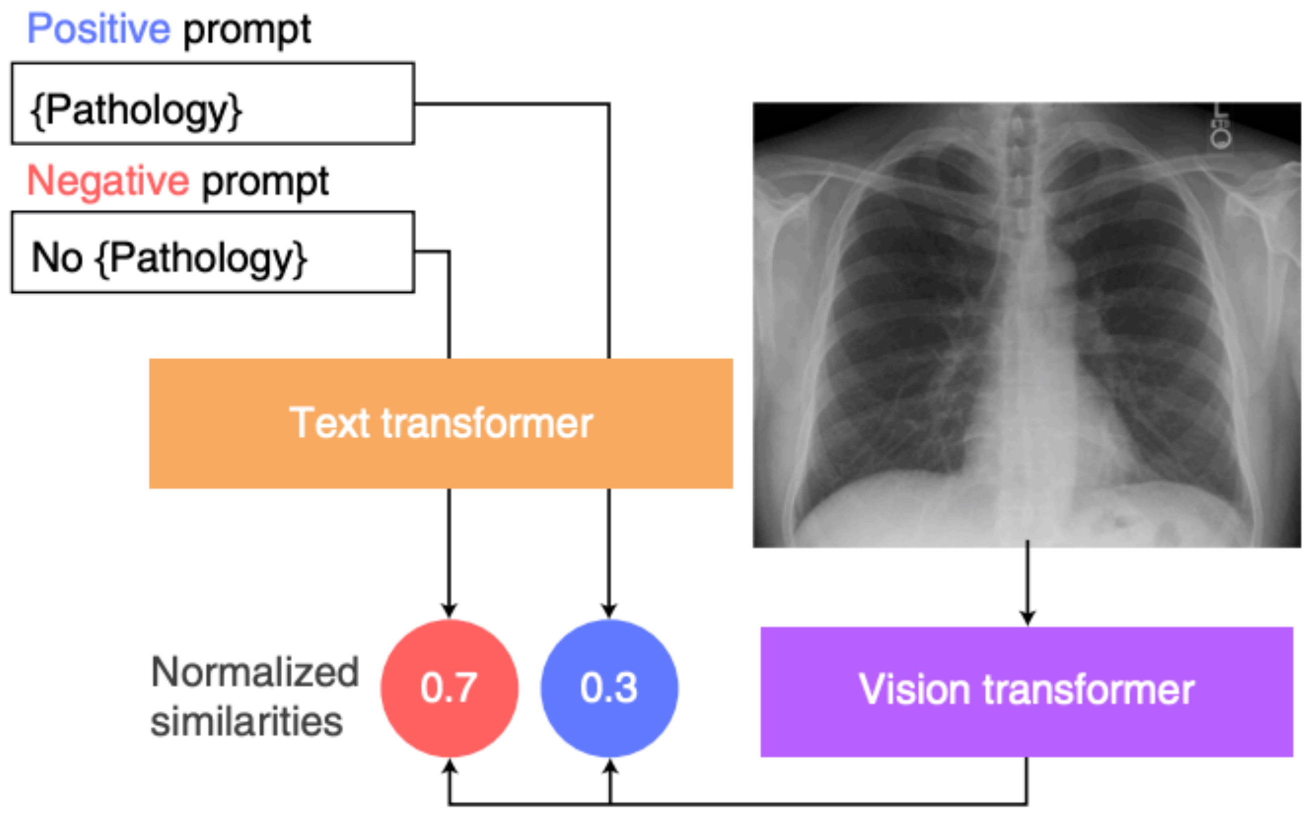
Evaluating Medical VLMs

Classification

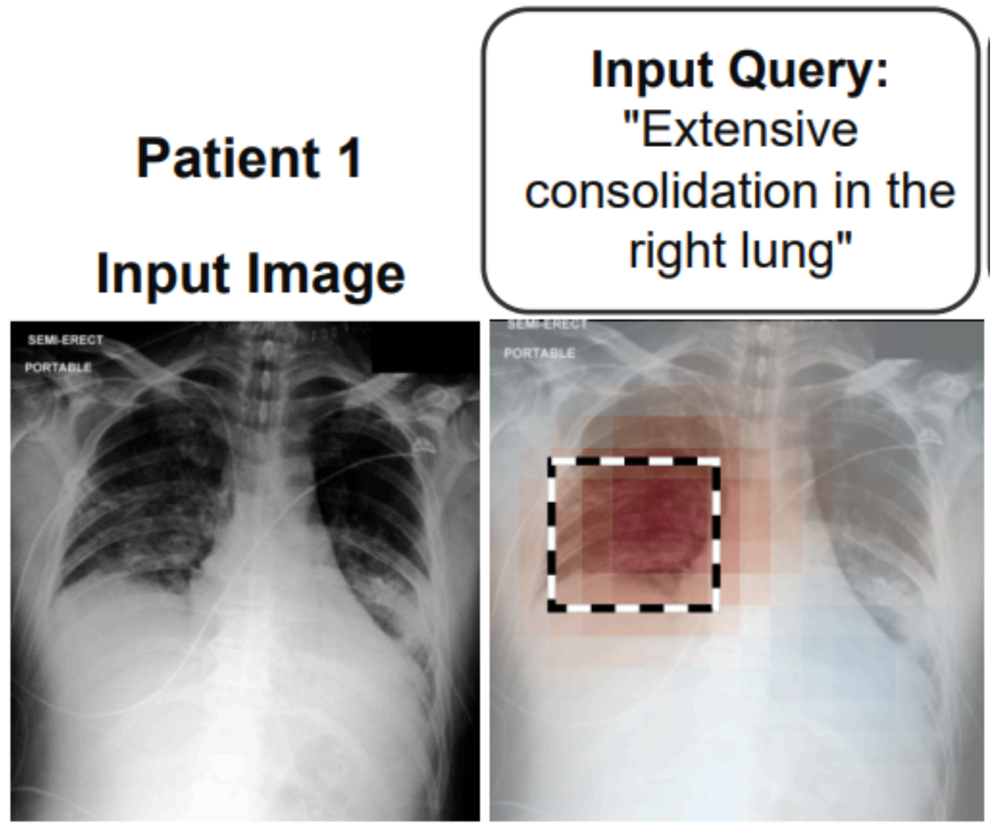


(*a*) ImageNet Pretraining (*b*) ConVIRT Pretraining

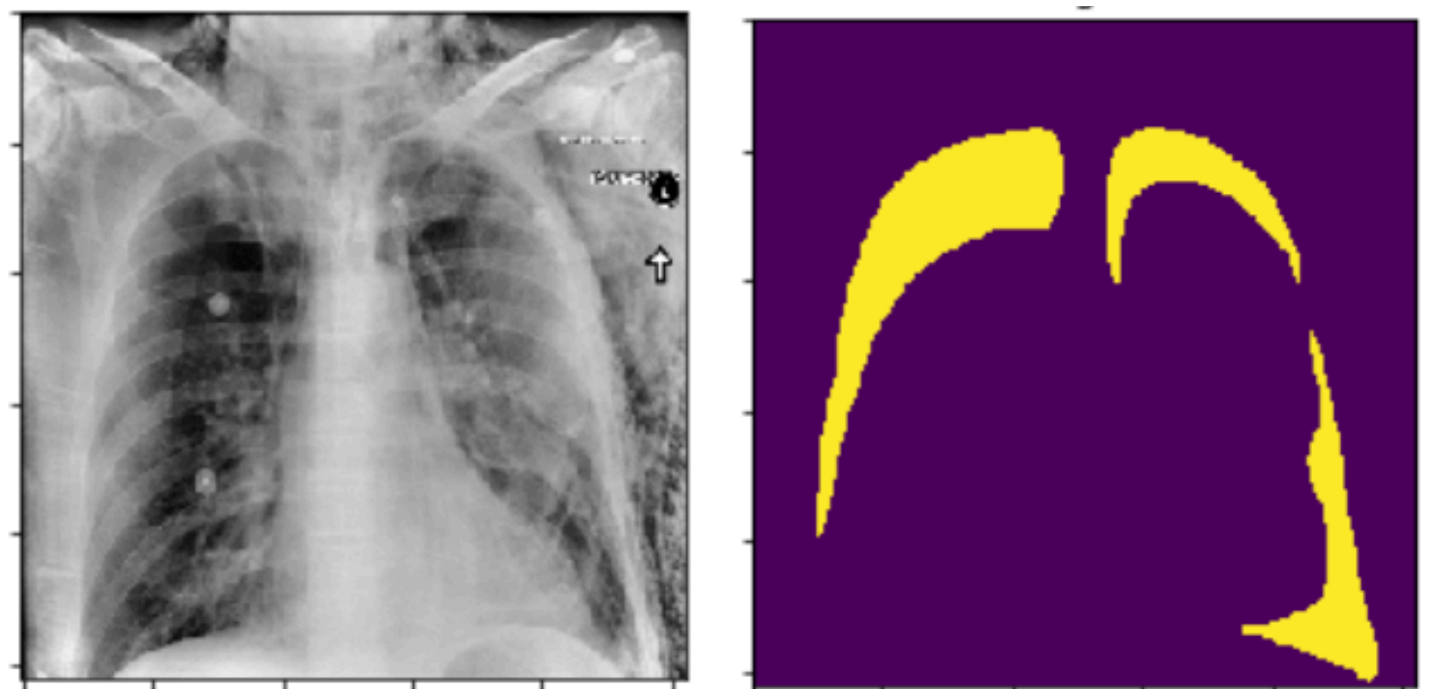
Zero-Shot Classification



Visual Grounding

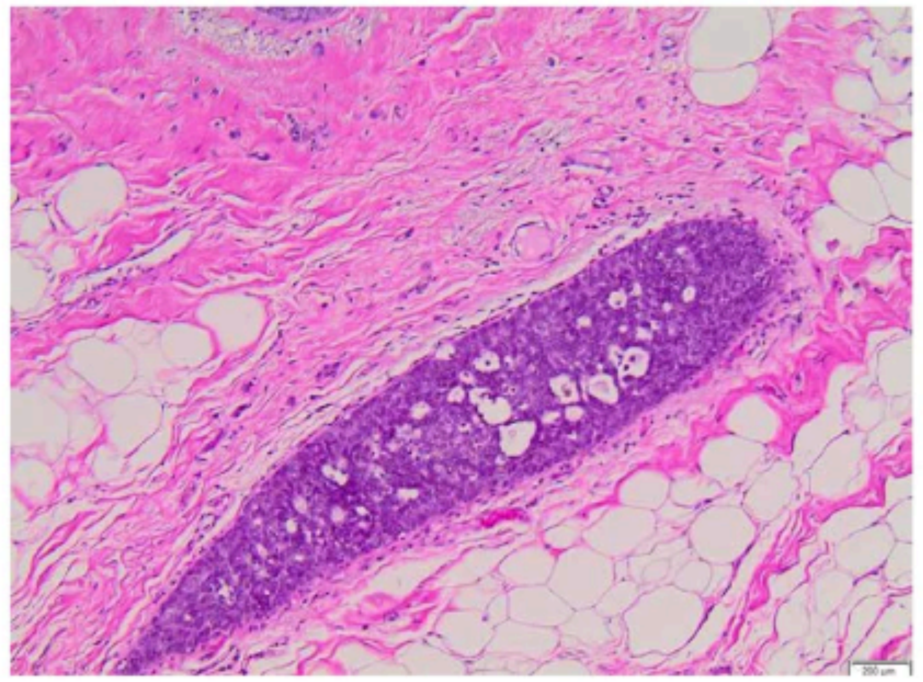


Segmentation



Text to Image Retrieval

Breast tumor surrounded by fat



Natural Language Inference

Sentence 1:

No pneumothorax is seen

Sentence 2:

Previously-seen pneumothorax is no longer visualized

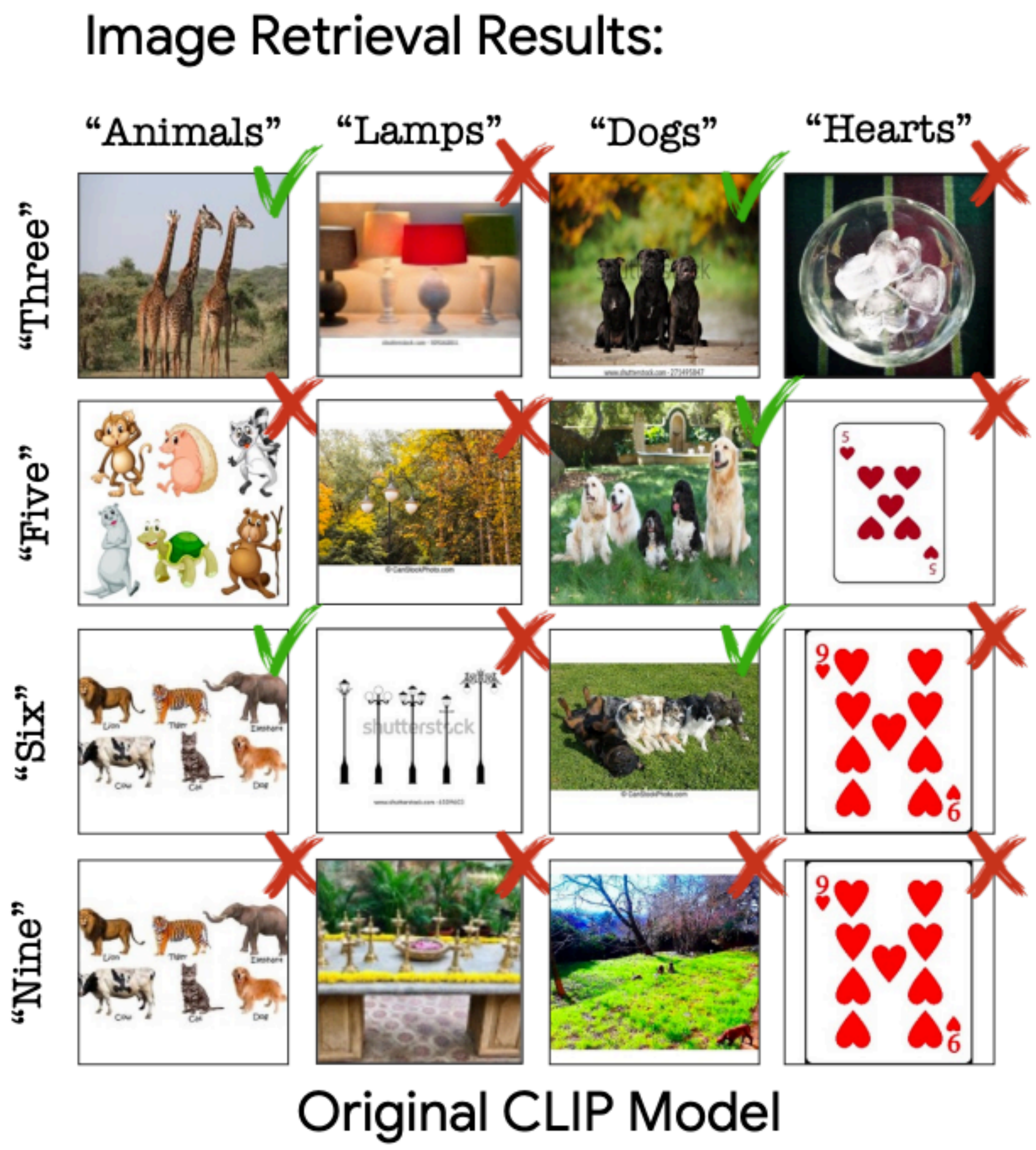
Type: ***Entailment***

Miura et al. “RadNLI: A natural language inference dataset for the radiology domain”
Zhang et al. "Contrastive Learning of Medical Visual Representations from Paired Images and Text"
Huang et al. “A visual-language foundation model for pathology image analysis using medical Twitter”
Tiu et al. “Expert-level detection of pathologies from unannotated chest X-ray images via self-supervised learning”
Boecking et al. “Making the Most of Text Semantics to Improve Biomedical Vision–Language Processing”

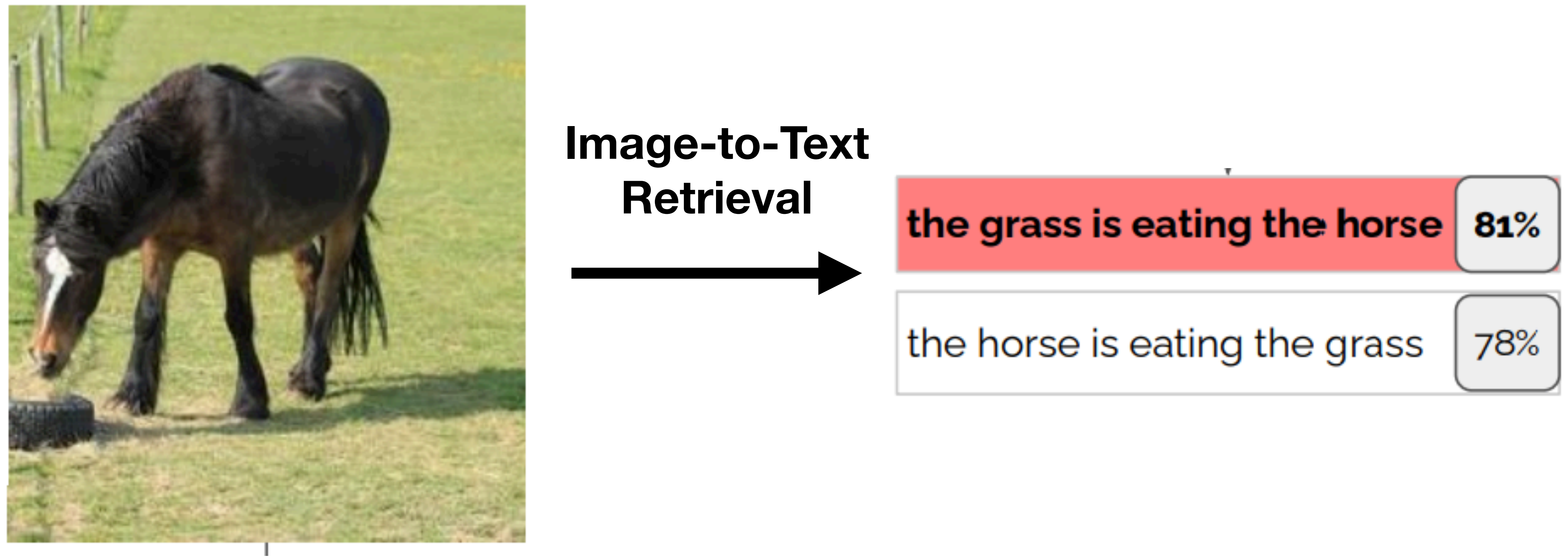
Part 3: Limitations

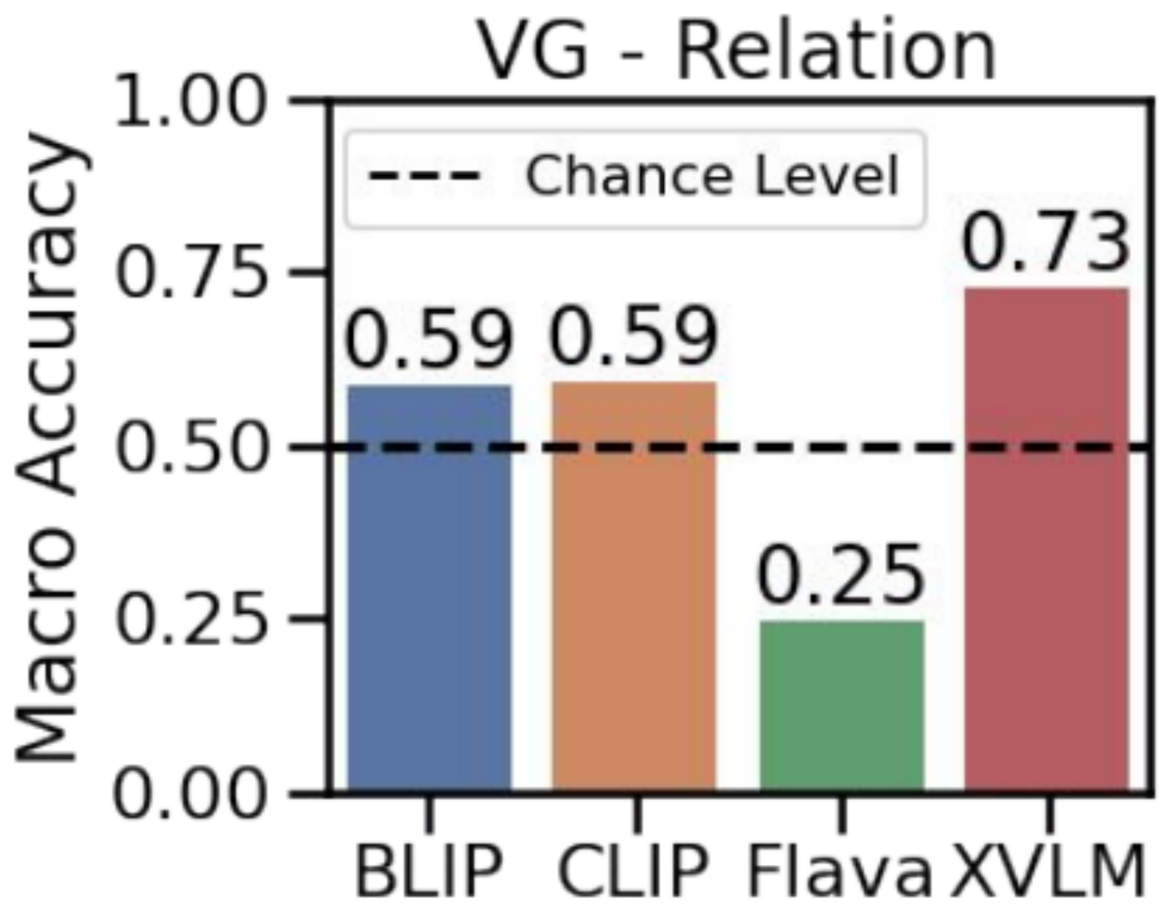
Limitations: Contrastive Training

Complex Patterns (e.g. counting)



Relational Understanding

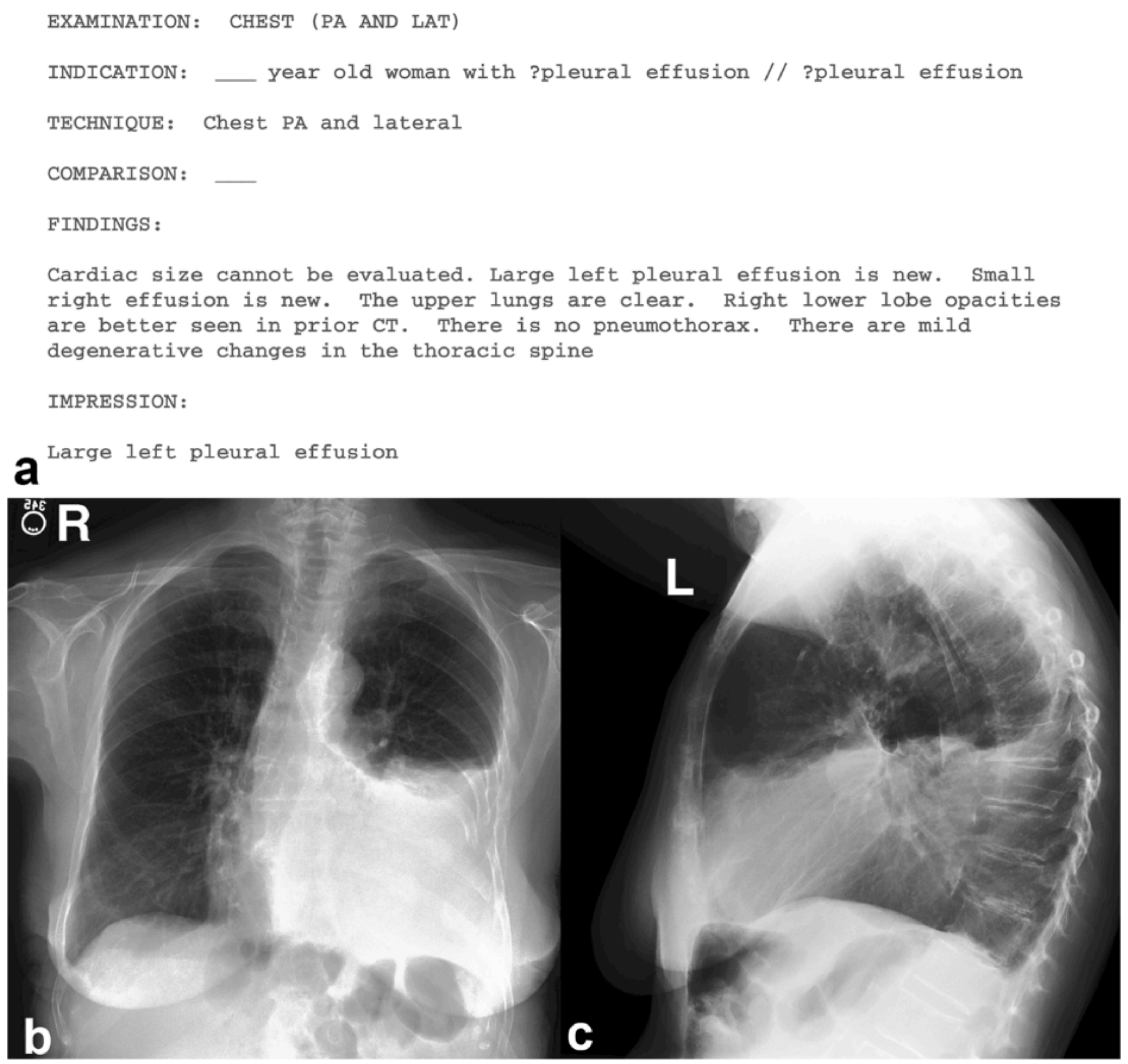




Paiss et al. "Teaching CLIP to Count to Ten"
Yuksekgonul et al. "When and Why Vision-Language Models Behave Like Bags-of-Words and What to Do About it?"

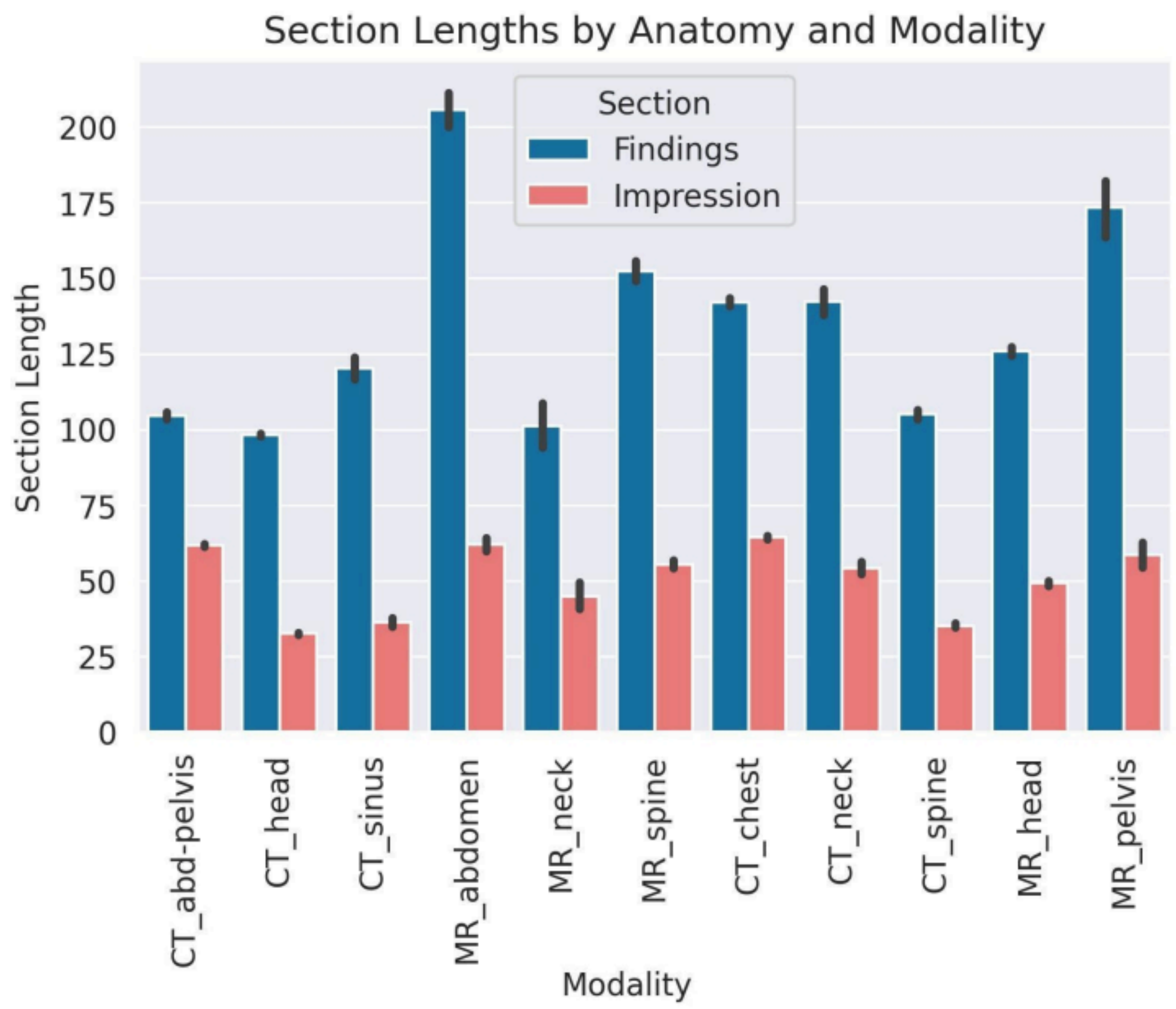
Limitations: Domain-Specific Challenges

Fine-Grained Visual Information



```
EXAMINATION:  CHEST (PA AND LAT)

INDICATION:  ___ year old woman with ?pleural effusion // ?pleural effusion

TECHNIQUE:  Chest PA and lateral

COMPARISON:  ___

FINDINGS:

Cardiac size cannot be evaluated. Large left pleural effusion is new.  Small
right effusion is new.  The upper lungs are clear.  Right lower lobe opacities
are better seen in prior CT.  There is no pneumothorax.  There are mild
degenerative changes in the thoracic spine

IMPRESSION:

Large left pleural effusion
```

Lengthy and Complex Text



Chen et al. “Toward Expanding the Scope of Radiology Report Summarization to Multiple Anatomies and Modalities"

Questions?