

Vision and Language



slides from: Daniel Fried, Yonatan Bisk, L-P Morency



Language Grounding

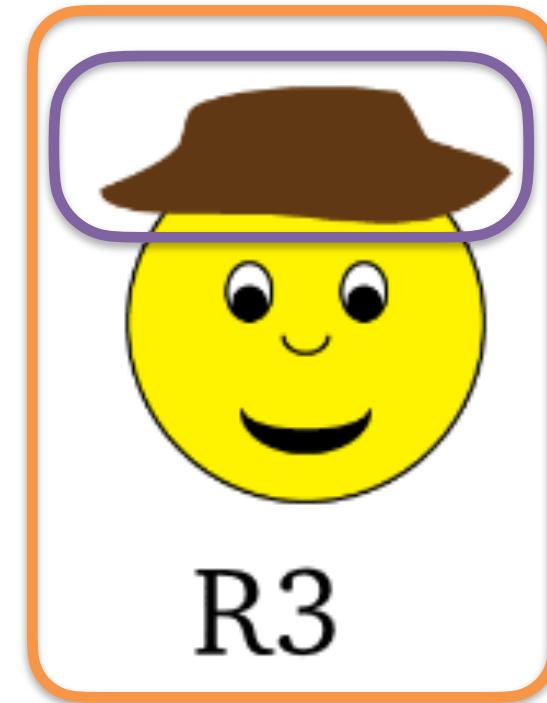
“Bob is wearing a hat” —————→ $\exists x . \text{hat}(x) \wedge \text{wears}(\text{bob}, x)$



R1



R2

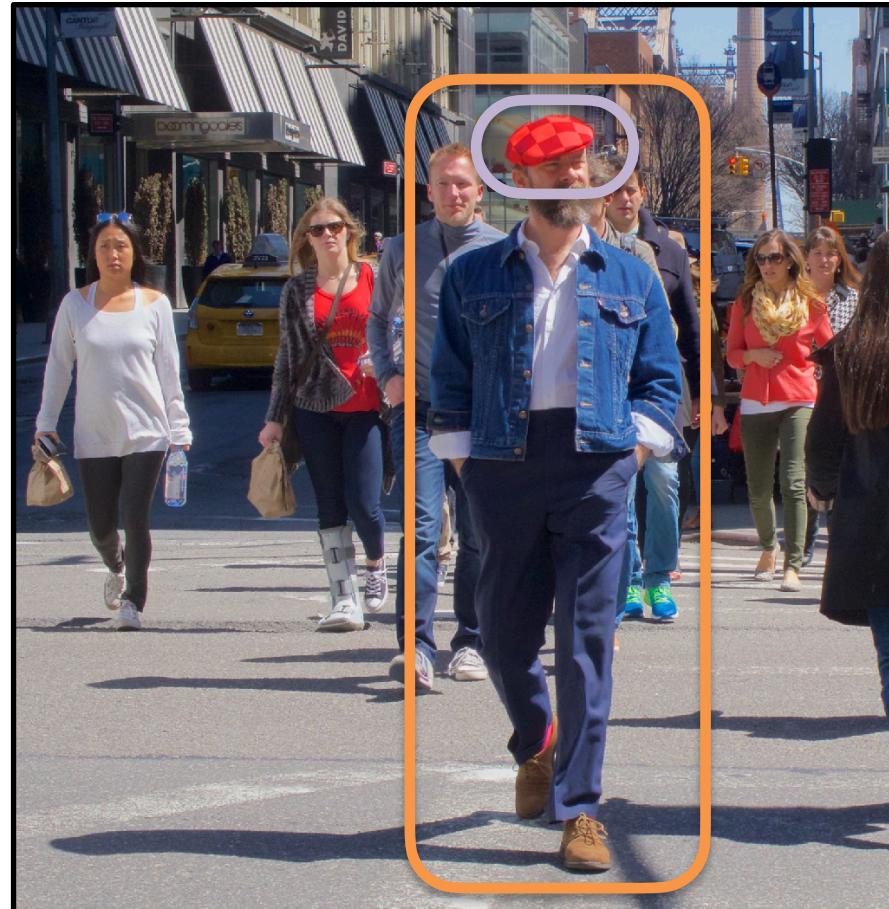


R3



Language Grounding

“Bob is wearing a hat” —————→ $\exists x . \text{hat}(x) \wedge \text{wears}(\text{bob}, x)$



x



bob



Representation Learning

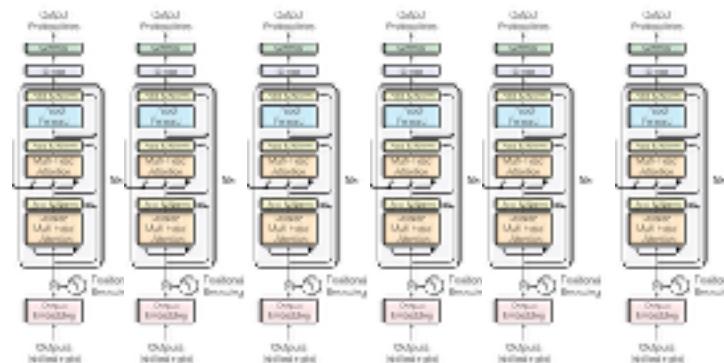
Representing language $\phi_l(x)$

“Bob is wearing a hat”

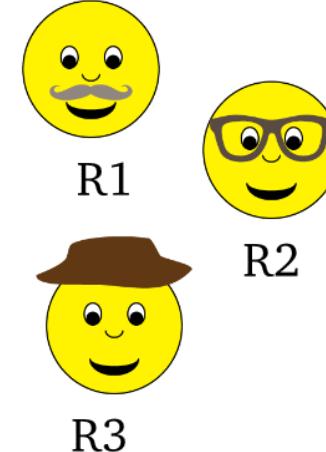


$$\begin{array}{c}
 \text{What} \qquad \text{states} \qquad \text{border} \qquad \text{Texas} \\
 \hline
 \frac{(S/(S\backslash NP))/N}{\lambda f.\lambda g.\lambda x.f(x) \wedge g(x)} \quad \frac{N}{\lambda x.\text{state}(x)} \quad \frac{(S\backslash NP)/NP}{\lambda x.\lambda y.\text{borders}(y,x)} \quad \frac{\text{Texas}}{NP} \\
 \hline
 \frac{S/(S\backslash NP)}{\lambda g.\lambda x.\text{state}(x) \wedge g(x)} \quad \frac{(S\backslash NP)}{\lambda y.\text{borders}(y,\text{texas})} \\
 \hline
 \frac{}{\lambda x.\text{state}(x) \wedge \text{borders}(x,\text{texas})}
 \end{array}$$

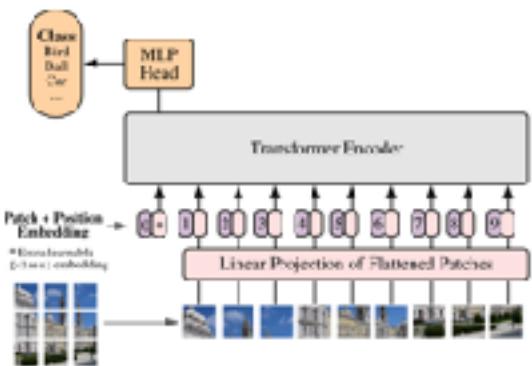
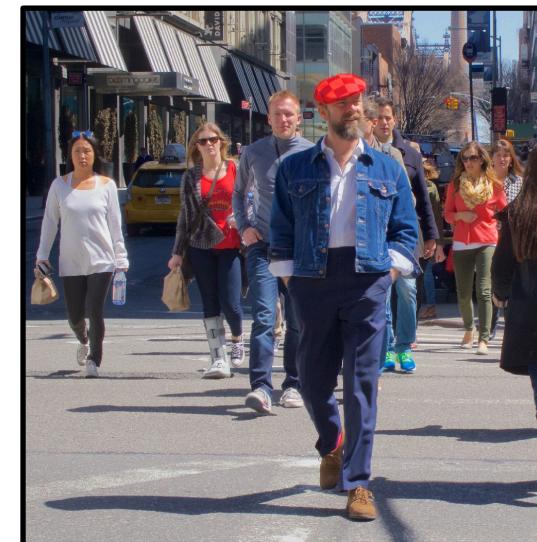
$\exists x . \text{hat}(x) \wedge \text{wears(bob, } x)$



Representing the world $\phi_w(i)$



	mustache?	glasses?	hat?
R1	yes	no	no
R2	no	yes	no
R3	no	no	yes





Grounding

Representing language $\phi_l(x)$

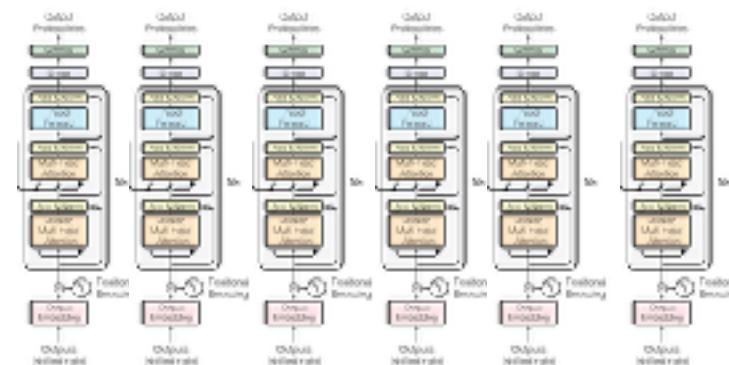
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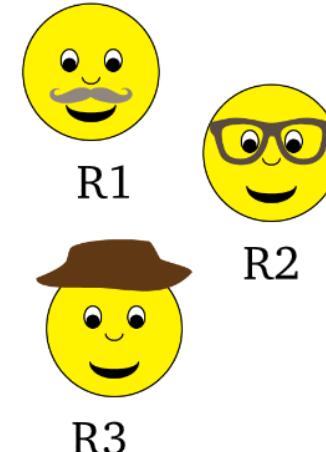
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 \hline
 \frac{S/(S\backslash NP)}{\lambda g.\lambda x.\text{state}(x) \wedge g(x)} \qquad \frac{(S\backslash NP)}{\lambda y.\text{borders}(y,\text{texas})} \\
 \hline
 \frac{}{\lambda x.\text{state}(x) \wedge \text{borders}(x,\text{texas})}
 \end{array}$$

\downarrow

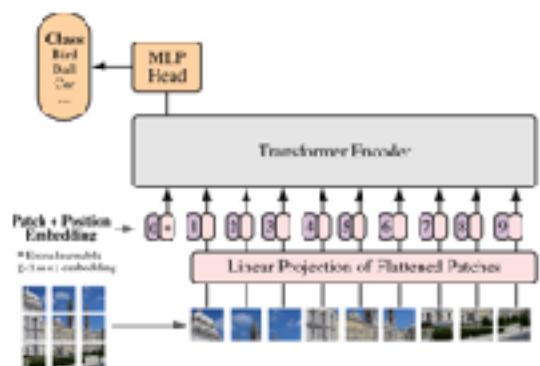
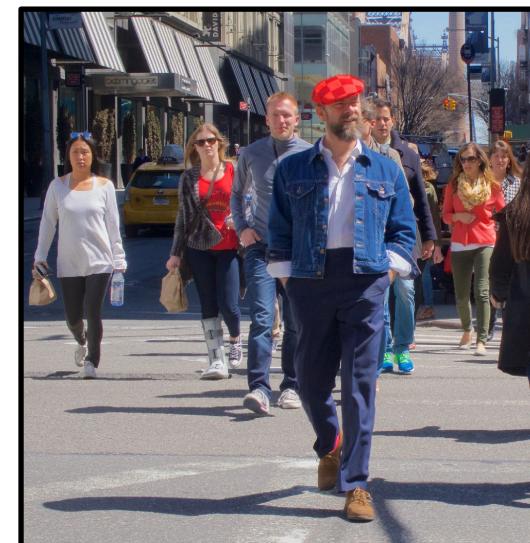
$\exists x . \text{hat}(x) \wedge \text{wears(bob, } x)$



Representing the world $\phi_w(i)$



	mustache?	glasses?	hat?
R1	yes	no	no
R2	no	yes	no
R3	no	no	yes





Vision-Language Tasks

- Image-text entailment

$$\phi_l(x) \stackrel{?}{=} \phi_w(i)$$



The left image contains twice the number of dogs as the right image, and at least two dogs in total are standing.

[NLVR2, Suhr et al. 2019]



右图中的人在发球，左图中的人在接球。

[MaRVL, Liu Fangyu et al. 2021]



Vision-Language Tasks

- Image-text entailment
- Question answering

$\text{ask}(\phi_l(x), \phi_w(i))$



Is this a vegetarian pizza?
[VQA, Antol et al. 2015]



Who is this mail for?
[VizWiz, Gurari et al.
2018]



Vision-Language Tasks

- Image-text entailment
- Question answering
- Image captioning $\arg \max_x \text{sim}(\phi_l(x), \phi_w(i))$



How would you describe this image to someone who can't see it?
“Grocery store photo of several bunches of bananas.”



Vision-Language Tasks

- Image-text entailment
- Question answering
- Image captioning $\arg \max_x \text{sim}(\phi_l(x), \phi_w(i))$



**What text should accompany this photo
in a Wikipedia article about bananas?**
*“Grocery store photo of several bunches
of bananas.”*



Vision-Language Tasks

- Image-text entailment
- Question answering
- Image captioning $\arg \max_x \text{sim}(\phi_l(x), \phi_w(i))$



Concadia, Kreiss et al. 2023

**What text should accompany this photo
in a Wikipedia article about bananas?**

*“Grocery store photo of several bunches
of bananas.”*

*“Cavendish bananas are the main commercial
banana cultivars sold in the world market.”*

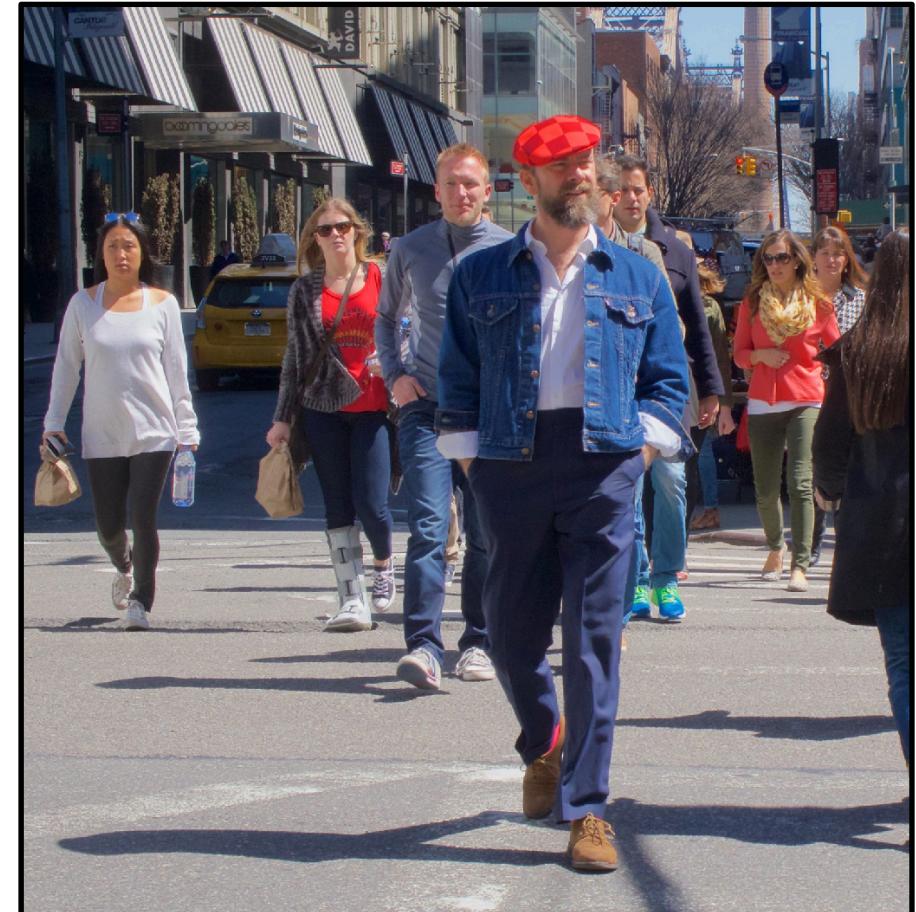


Vision-Language Tasks

- Image-text entailment
- Question answering
- Image captioning
- Referring expression resolution

$$\arg \max_{i' \in i} \text{sim}(\phi_l(x), \phi_w(i'))$$

“The guy with the hat”





Vision-Language Tasks

- Image-text entailment
- Question answering
- Image captioning
- Referring expression resolution

$$\arg \max_{i' \in i} \text{sim}(\phi_l(x), \phi_w(i'))$$

“The guy with the hat”





Vision-Language Tasks

- Image-text entailment
- Question answering
- Image captioning
- Referring expression resolution

$$\arg \max_{i' \in i} \text{sim}(\phi_l(x), \phi_w(i'))$$

“The guy with the hat”





Vision-Language Tasks

- Image-text entailment
- Question answering
- Image captioning
- Referring expression resolution
- Image generation

$$\arg \max_i \text{sim}(\phi_l(x), \phi_w(i))$$

An illustrated scene in a classroom setting focused on Natural Language Processing (NLP). The classroom is modern with a large blackboard at the front, displaying diagrams of neural networks and examples of NLP tasks like text classification and machine translation. There are students of various descents sitting at desks with laptops open, showing code and language statistics. A professor, a Middle-Eastern woman, stands at the front with a pointer, gesturing towards the blackboard. Some of the students are taking notes, while others are discussing amongst themselves. The room has large windows with sunlight streaming in, and posters on the wall about AI and linguistics.

You
generate me an image as an example of image generation for an nlp class

ChatGPT

A detailed illustration of a classroom scene. In the foreground, several students are seated at desks, each with a laptop open, facing away from the camera. In the background, a teacher, a woman with dark hair in a blue dress, stands at the front of the room, pointing towards a large chalkboard. The chalkboard is filled with diagrams and text related to NLP, including neural network structures, flowcharts, and tables. To the left of the chalkboard, there's a whiteboard with some writing. The room has large windows on the right side, letting in sunlight. On the walls, there are posters and charts related to AI and linguistics. A potted plant sits on a shelf near the window.

Here is an image generated as an example for your NLP class.

◀ ▶ ⌂ ⌃



Vision-Language Tasks

- Image-text entailment
- Question answering
- Image captioning
- Referring expression resolution
- Image generation
- Conversational question answering
- Video question answering, captioning
- Instruction following



Methods

- Language representations
- Image representations
- Joint embedding spaces
- Multimodal transformers
- Neurosymbolic / code as a bottleneck



Image Representation: CNNs

Goal: building more abstract, hierarchical visual representations

Key advantages:

- 1) Inspired from visual cortex
- 2) Encourages visual abstraction
- 3) Exploits *translation invariance*
- 4) Kernels/templates are learned
- 5) Fewer parameters than MLP

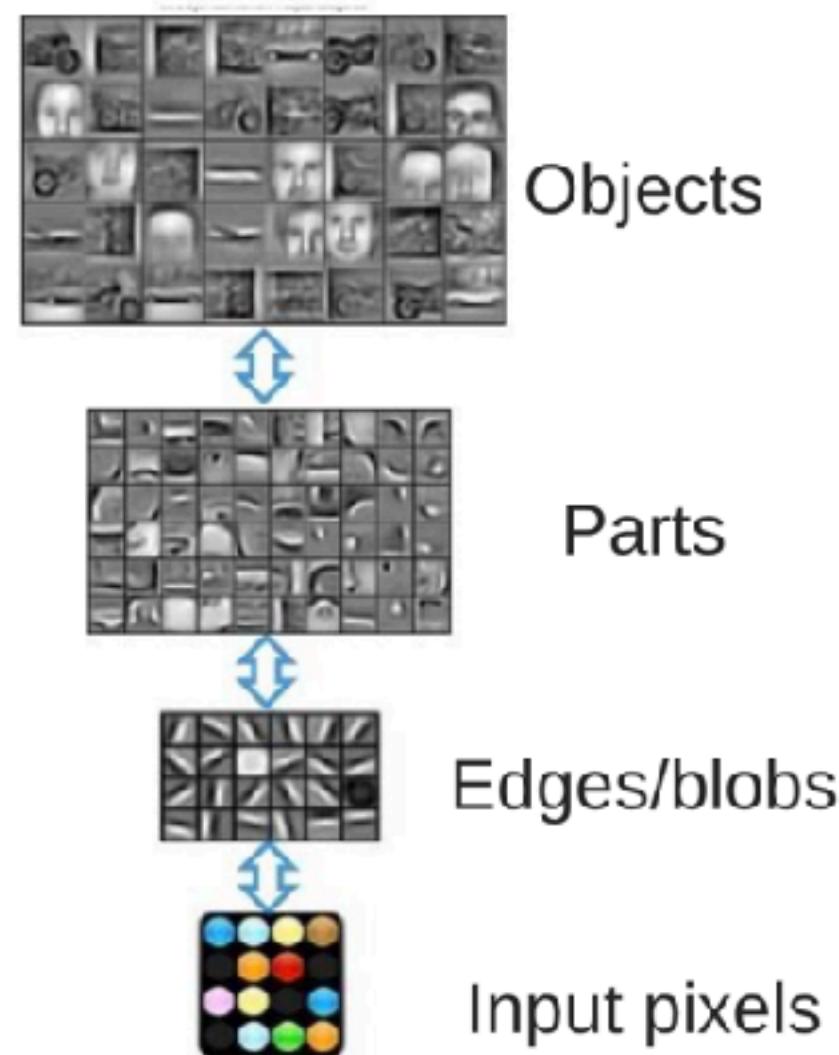




Image Representation: CNNs



2 Data Points – Which one is up?

- MLP can easily learn this task (possibly with only 1 neuron!)



What happens if the face is slightly translated?

- The model should still be able to classify it

Conventional MLP models are not translation invariant!

- But CNNs are kernel-based, which helps with translation invariance and reduce number of parameters



CNNs: Convolution

1 <small>x1</small>	1 <small>x0</small>	1 <small>x1</small>	0	0
0 <small>x0</small>	1 <small>x1</small>	1 <small>x0</small>	1	0
0 <small>x1</small>	0 <small>x0</small>	1 <small>x1</small>	1	1
0	0	1	1	0
0	1	1	0	0

Image

4		

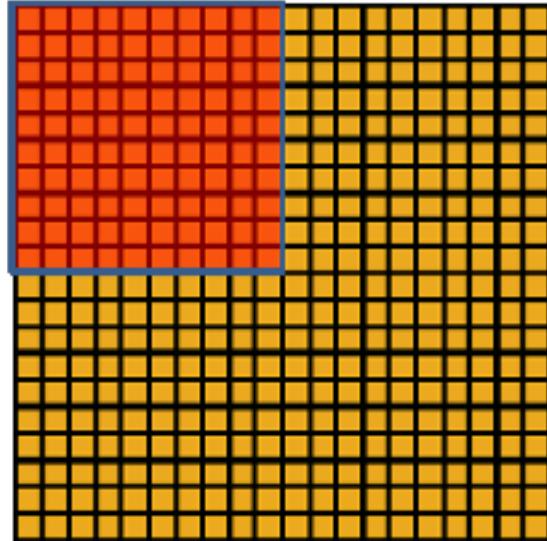
Convolved
Feature

Filter:

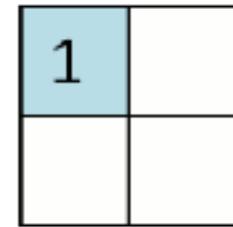
1	0	1
0	1	0
1	0	1



CNNs: Pooling



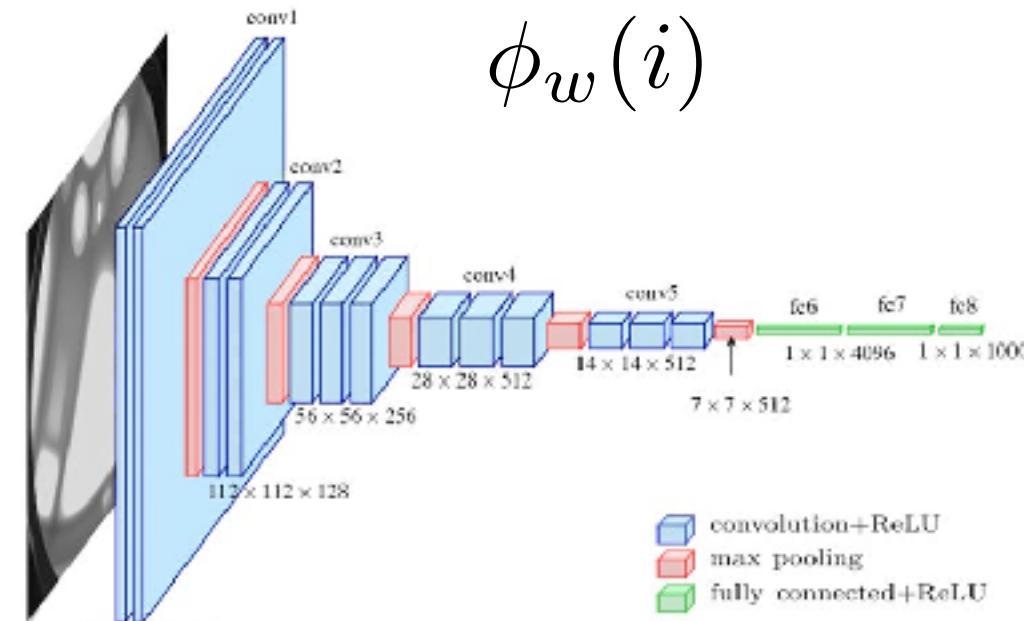
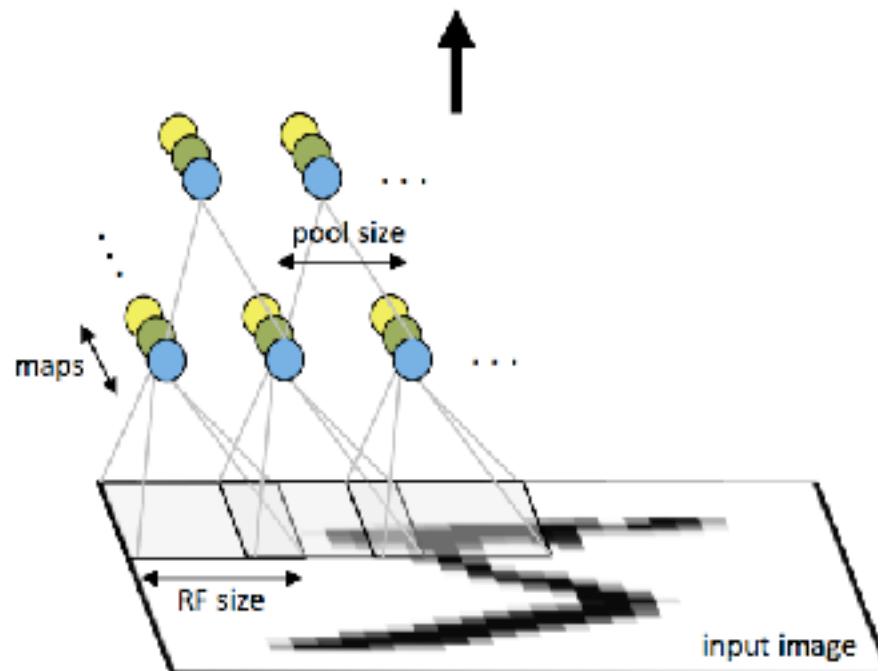
Convolved
feature



Pooled
feature



Multilayer CNNs





CNN Explainer

<https://poloclub.github.io/cnn-explainer/>



Vision Transformer

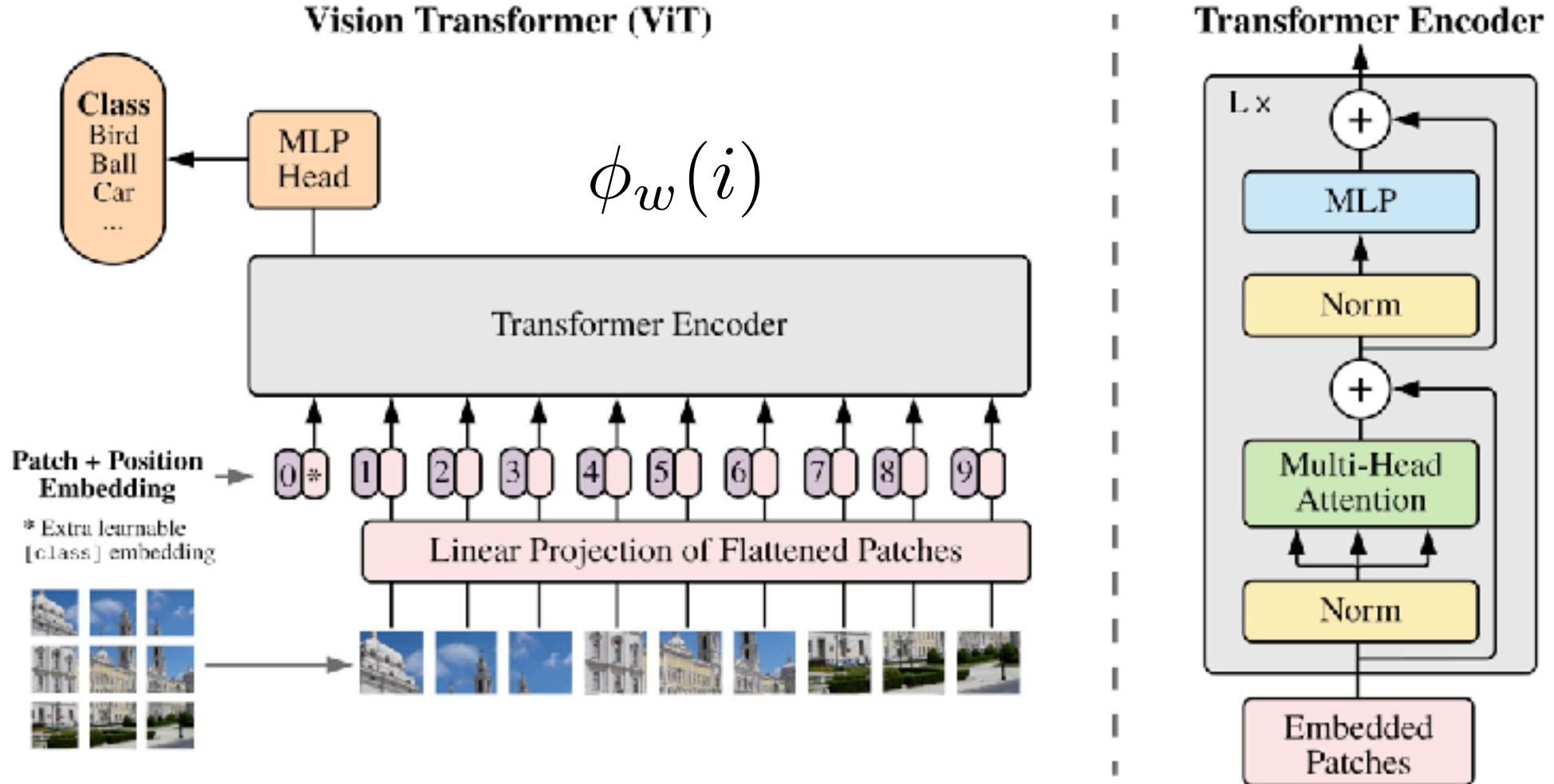




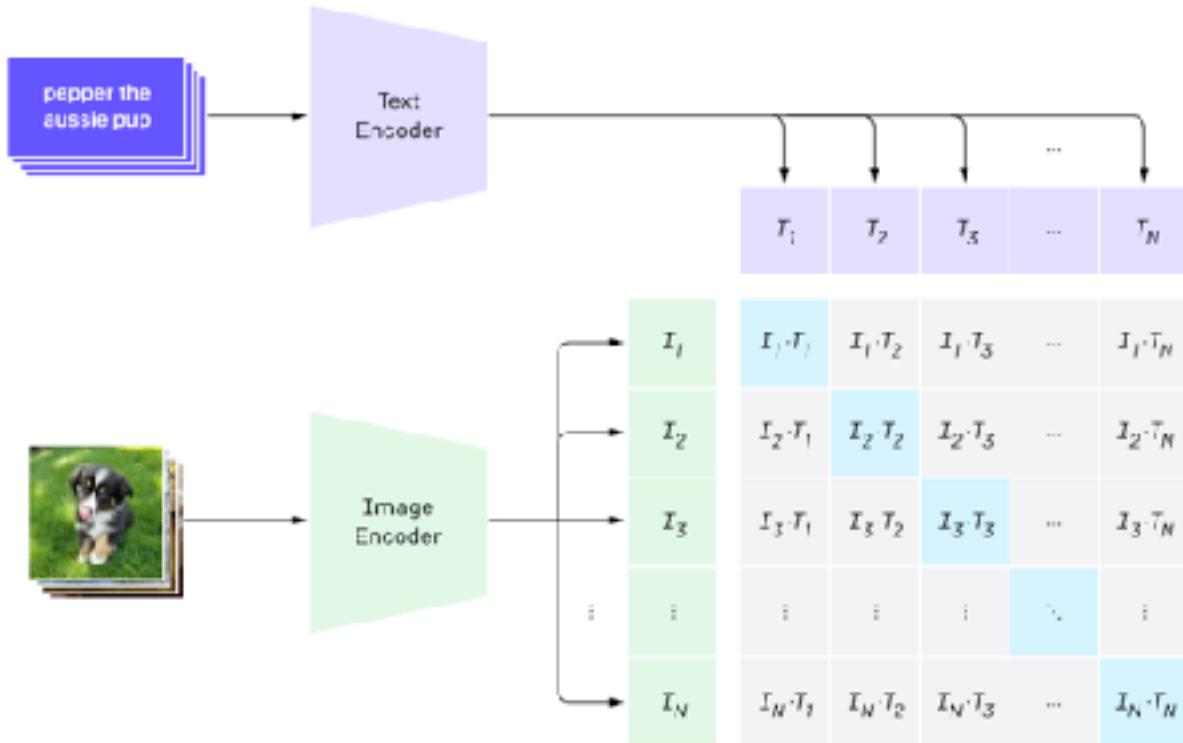
Image-Text Matching

- Idea: learn a shared representational space of images and text
- I.e., representation of sentence x paired with image i should be similar to one another $\phi_l(x) \approx \phi_w(i)$
- CLIP (Contrastive Language-Image Pre-Training), Radford et al.
2021



CLIP

1. Contrastive pre-training



```
# image_encoder - ResNet or Vision Transformer
# text_encoder - CBOW or Text Transformer
# I[n, h, w, c] - minibatch of aligned images
# T[n, l] - minibatch of aligned texts
# W_i[d_i, d_e] - learned proj of image to embed
# W_t[d_t, d_e] - learned proj of text to embed
# t - learned temperature parameter

# extract feature representations of each modality
I_f = image_encoder(I) #[n, d_i]
T_f = text_encoder(T) #[n, d_t]

# joint multimodal embedding [n, d_e]
I_e = l2_normalize(np.dot(I_f, W_i), axis=1)
T_e = l2_normalize(np.dot(T_f, W_t), axis=1)

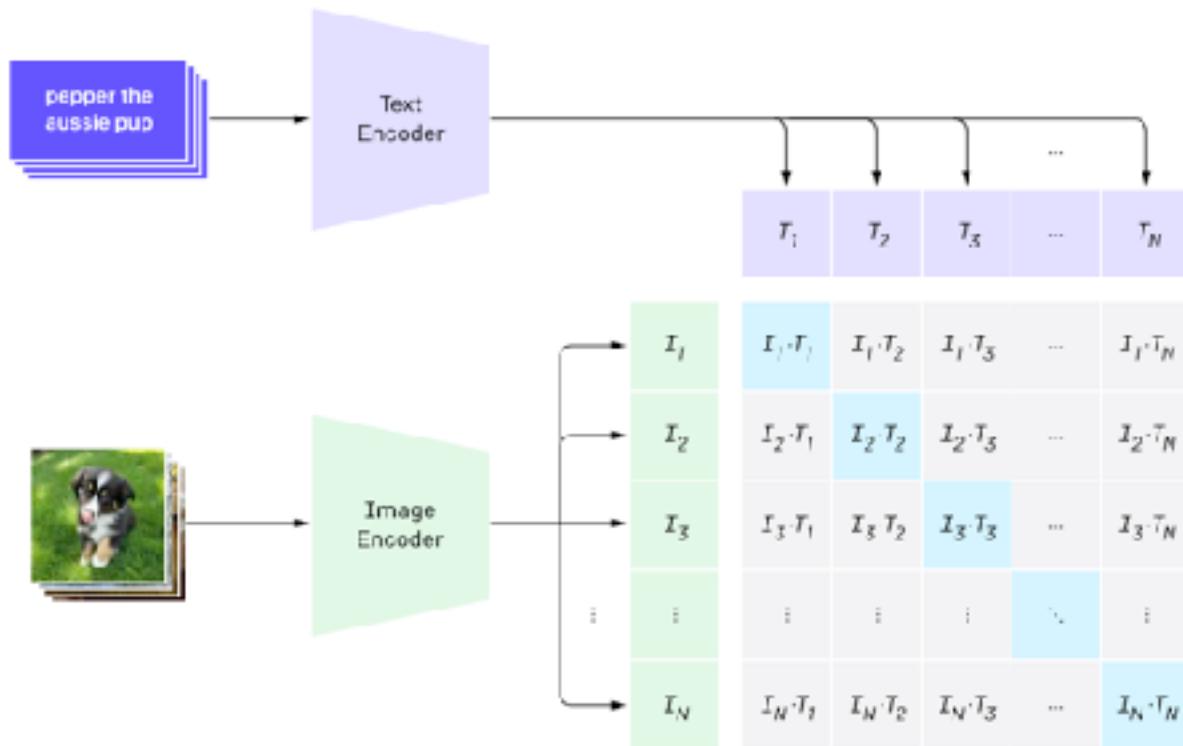
# scaled pairwise cosine similarities [n, n]
logits = np.dot(I_e, T_e.T) * np.exp(t)

# symmetric loss function
labels = np.arange(n)
loss_i = cross_entropy_loss(logits, labels, axis=0)
loss_t = cross_entropy_loss(logits, labels, axis=1)
loss = (loss_i + loss_t) / 2
```

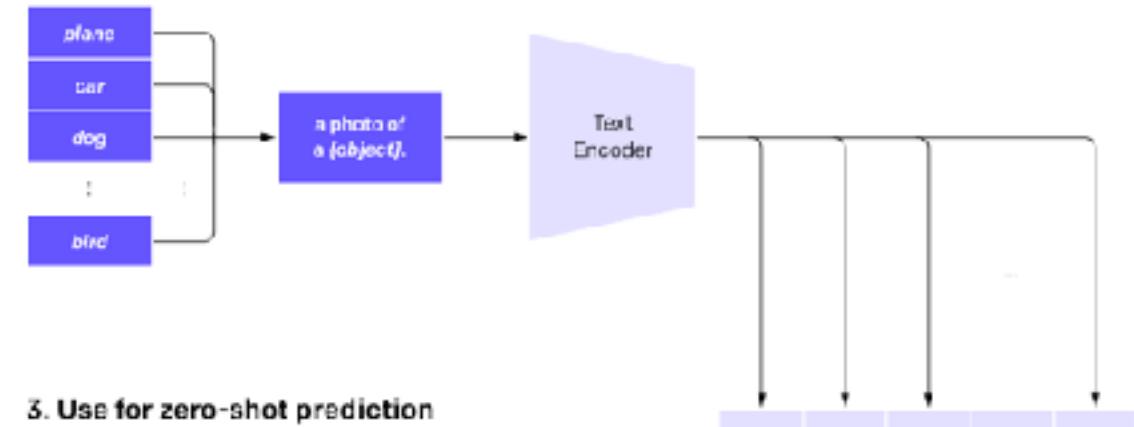
CLIP



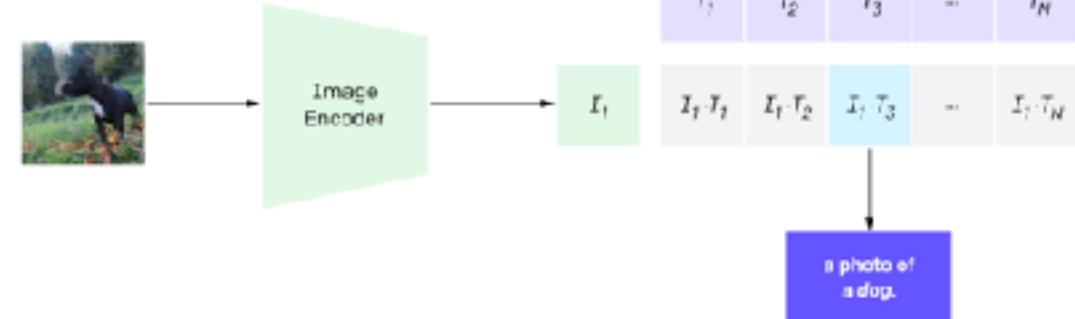
1. Contrastive pre-training



2. Create dataset classifier from label text



3. Use for zero-shot prediction





CLIP Applied: Image-Text Retrieval

E.g., retrieve an image given a piece of text:

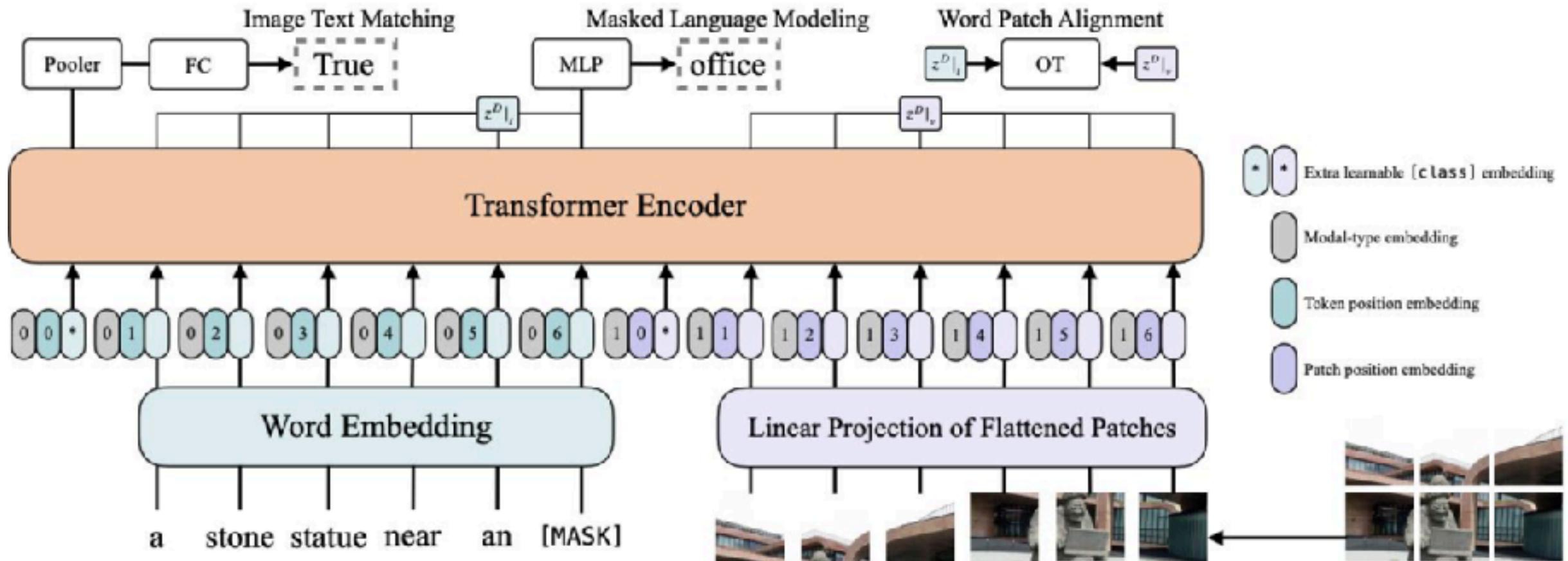
$$\arg \max_{i \in \mathcal{I}} \phi_l(x) \cdot \phi_w(i)$$

<https://rom1504.github.io/clip-retrieval/>



Joint Encoding: Multimodal Transformers

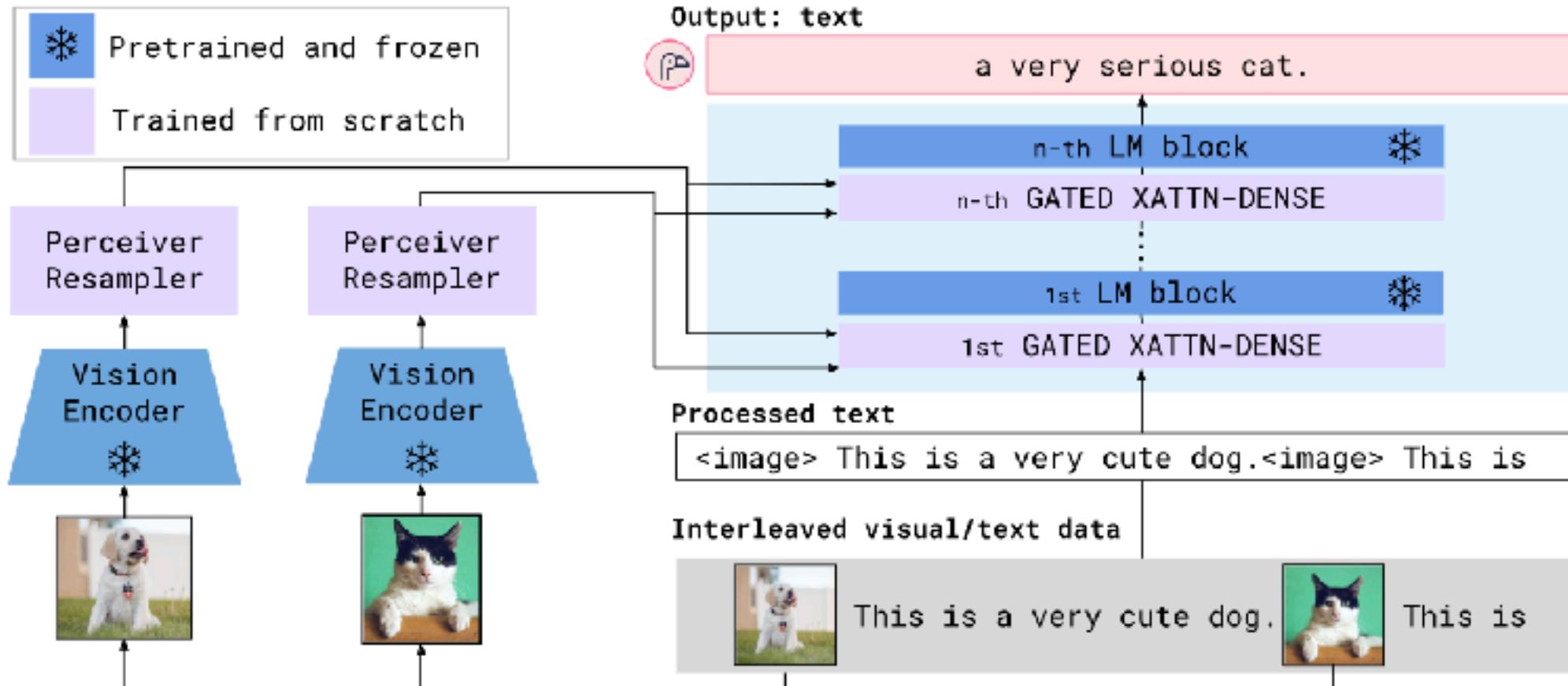
ViLT (Kim et al. 2021), encoder-only model (like BERT)





Joint Encoding: Multimodal Transformers

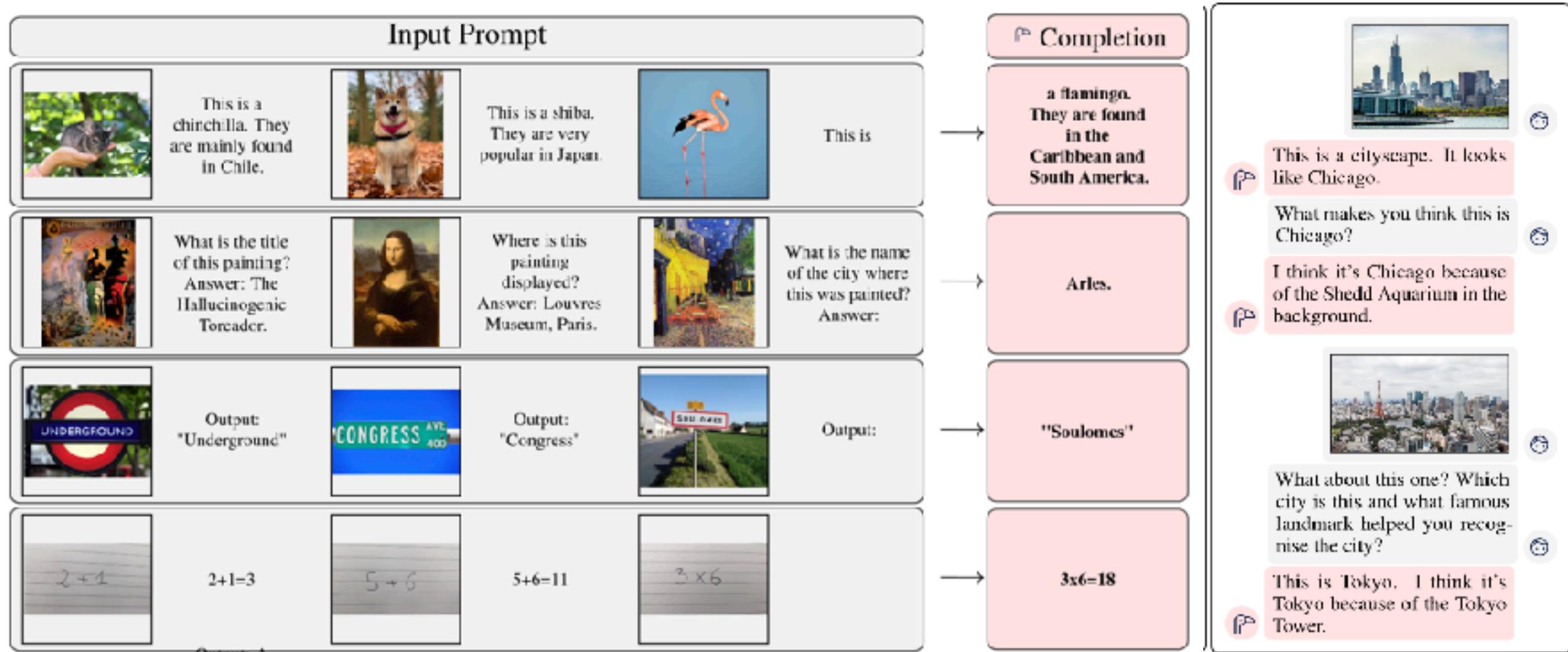
Flamingo, Alayrac et al. 2022





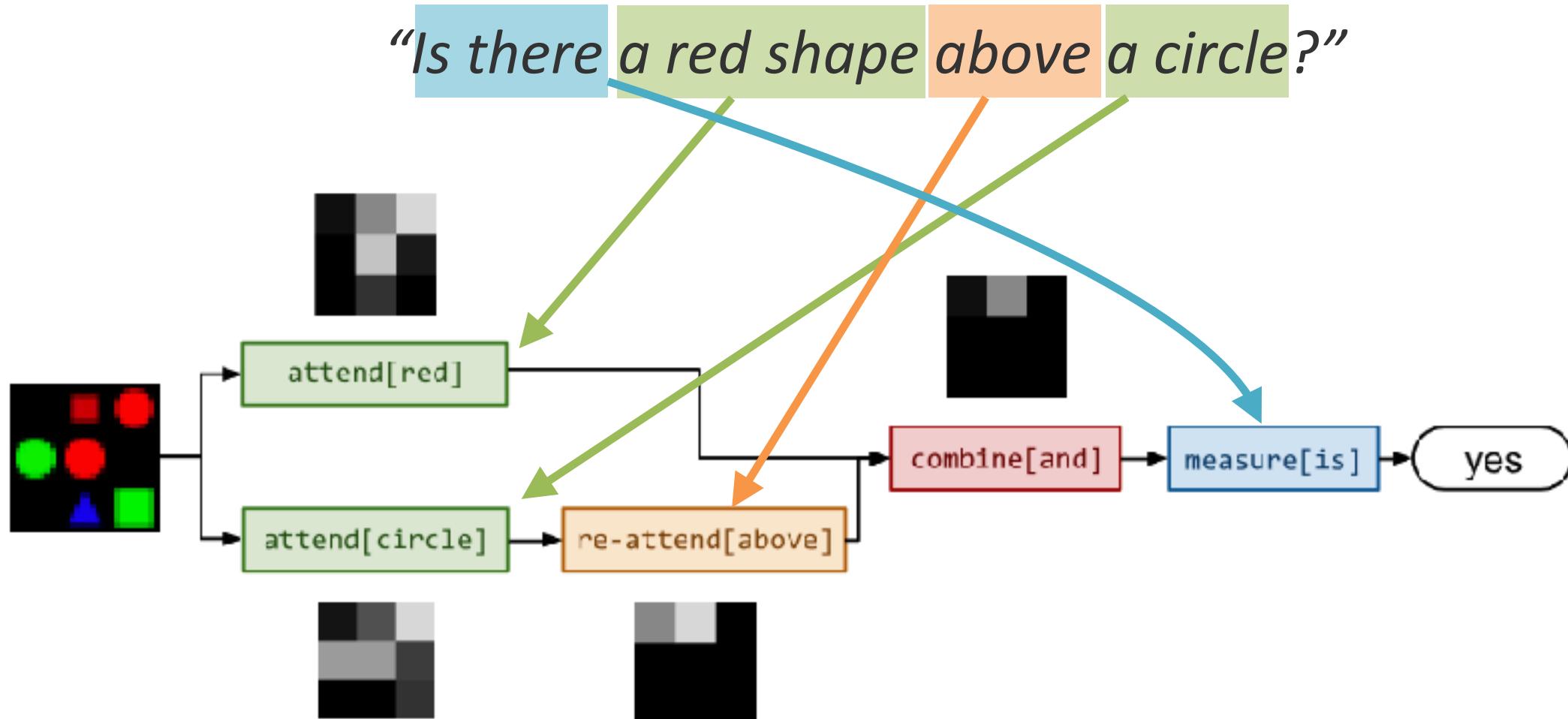
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Flamingo, Alayrac et al. 2022





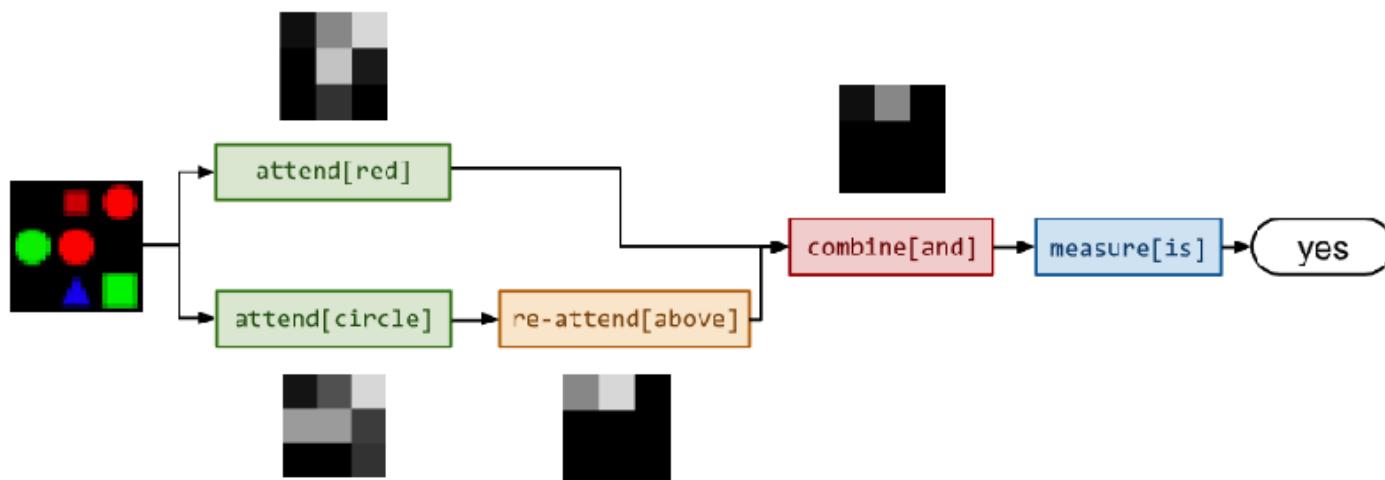
Neuromodular Approaches





Neuromodular Approaches

“Is there a red shape above a circle?”

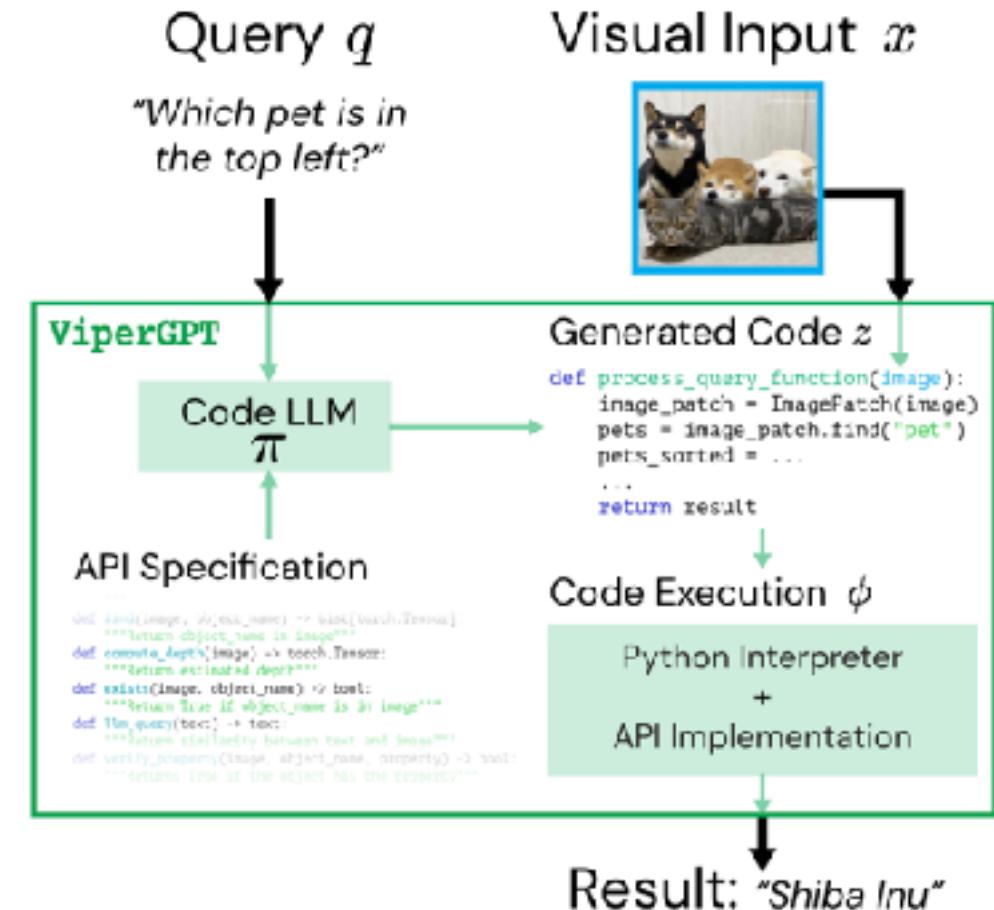


- Map x to some structured representation $\phi_l(x)$
- Manipulate image $\phi_w(i)$ according to components of this structured representation



Neuromodular Approaches

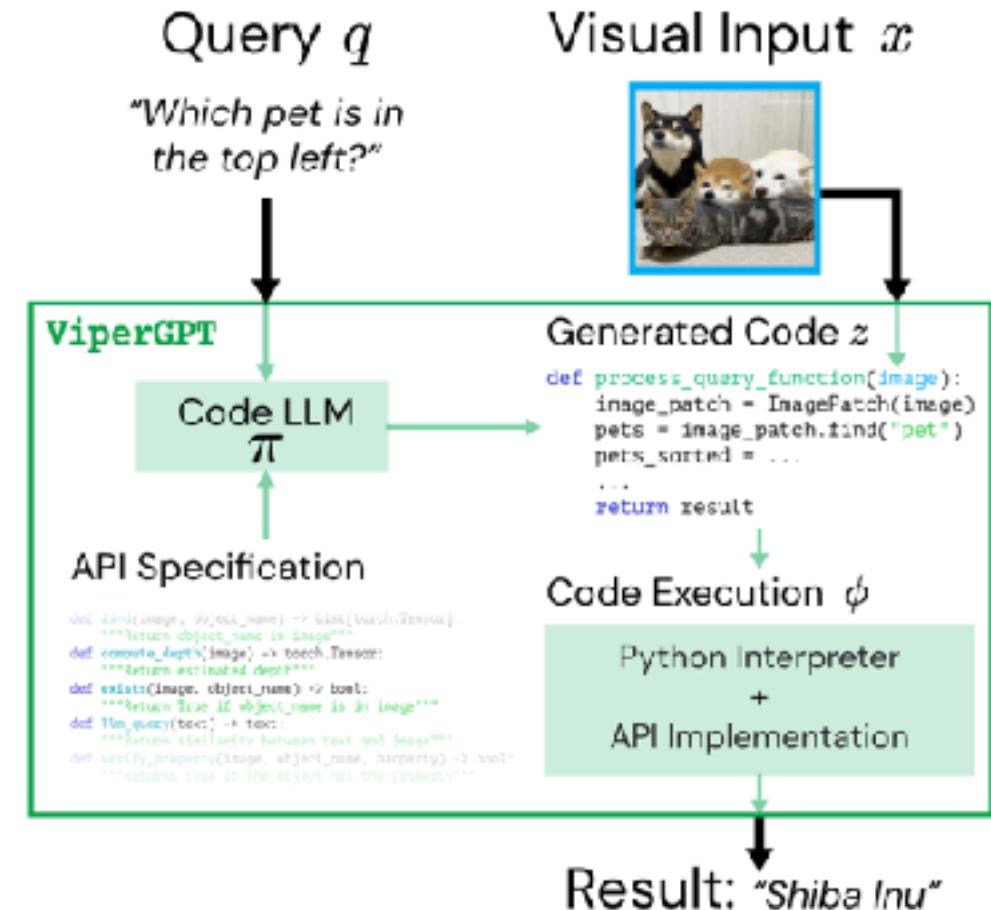
- Text representation: executable python code
- Image representation: pixels (also assume access to some computer vision algorithms)
- Grounding: executing python code on image representations





Neuromodular Approaches

With sufficiently powerful code LLMs (e.g., Codex) and access to an API that can operate on top of images (or other modalities), no domain-specific or multimodal training is necessary





Neuromodular Approaches

Query: How many muffins can each kid have for it to be fair?



Neuromodular Approaches

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Generated Code

```
def execute_command(image):
    image_patch = ImagePatch(image)
    muffin_patches = image_patch.find("muffin")
    kid_patches = image_patch.find("kid")
    return str(len(muffin_patches) // len(kid_patches))
```



Neuromodular Approaches

Query: How many muffins can each kid have for it to be fair?



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```

Execution

```
muffin_patches =
image_patch.find("muffin")
```



```
kid_patches =
image_patch.find("kid")
```

```
kid_patches =
image_patch.find("kid")
```



- $\text{len}(\text{muffin_patches})=8$
- $\text{len}(\text{kid_patches})=2$

$$8//2 = 4$$

Result: 4



Neuromodular Approaches

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kid_patches =
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```



► len(muffin_patches)=8
► len(kid_patches)=2

$$8/2 = 4$$

Result: 4

Query: Return the two kids that are furthest from the woman right before she hugs the girl



```
def execute_command(video):
    video_segment = VideoSegment(video)
    hug_detected = False
    for i, frame in enumerate(video_segment.frame_iterator()):
        if frame.exists("woman") and frame.exists("girl") and \
            frame.simple_query("Is the woman hugging the girl?") == "yes":
            hug_detected = True
            break
    if hug_detected:
        index_frame = i - 1
        frame_of_interest = ImagePatch(video_segment, index_frame)
        woman_patches = frame_of_interest.find("woman")
        woman_patch = woman_patches[0]
        kid_patches = frame_of_interest.find("kid")
        kid_patches.sort(key=lambda kid: distance(kid, woman_patch))
        kid_patch_1 = kid_patches[-1]
        kid_patch_2 = kid_patches[-2]
        return [kid_patch_1, kid_patch_2]
```



Neuromodular Approaches

Query: How many muffins can each kid have for it to be fair?



Generated Code

```
def execute_command(image):
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    kid_patches = image_patch.find("kid")
    return str(len(muffin_patches) // len(kid_patches))
```

Execution

```
muffin_patches =
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```



```
kid_patches =
image_patch.find("kid")
```

```
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Result: 4

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    if hug_detected:
        index_frame = i - 1
        frame_of_interest = ImagePatch(video_segment, index_frame)
        woman_patches = frame_of_interest.find("woman")
        woman_patch = woman_patches[0]
        kid_patches = frame_of_interest.find("kid")
        kid_patches.sort(key=lambda kid: distance(kid, woman_patch))
        kid_patch_1 = kid_patches[-1]
        kid_patch_2 = kid_patches[-2]
    return [kid_patch_1, kid_patch_2]
```

► hug_detected=True
► frame=



► frame_of_interest=



► kid_patches=



sort(...distance...)
► kid_patches=



Result:



Neuromodular Approaches

Query: What color do you get if you combine the colors of the viper and the flower?



```
def execute_command(image):
    image_patch = ImagePatch(image)
    viper_patches = image_patch.find("viper")
    flower_patches = image_patch.find("flower")
    viper_patch = viper_patches[0]
    flower_patch = flower_patches[0]
    viper_color = viper_patch.simple_query("What color is the viper?")
    flower_color = flower_patch.simple_query("What color is the flower?")
    color = llm_query(f"What color do you get if you combine the colors
        {viper_color} and {flower_color}?")
    return color
```

► viper_patch=

► flower_patch=

► viper_color='blue'

► flower_color='red'

► color='purple'

Result: “purple”



Drawback: Context-Dependence

“Is the potted plant to the right of the bench?”





Drawback: Context-Dependence

“Is the potted plant to the right of the bench?”

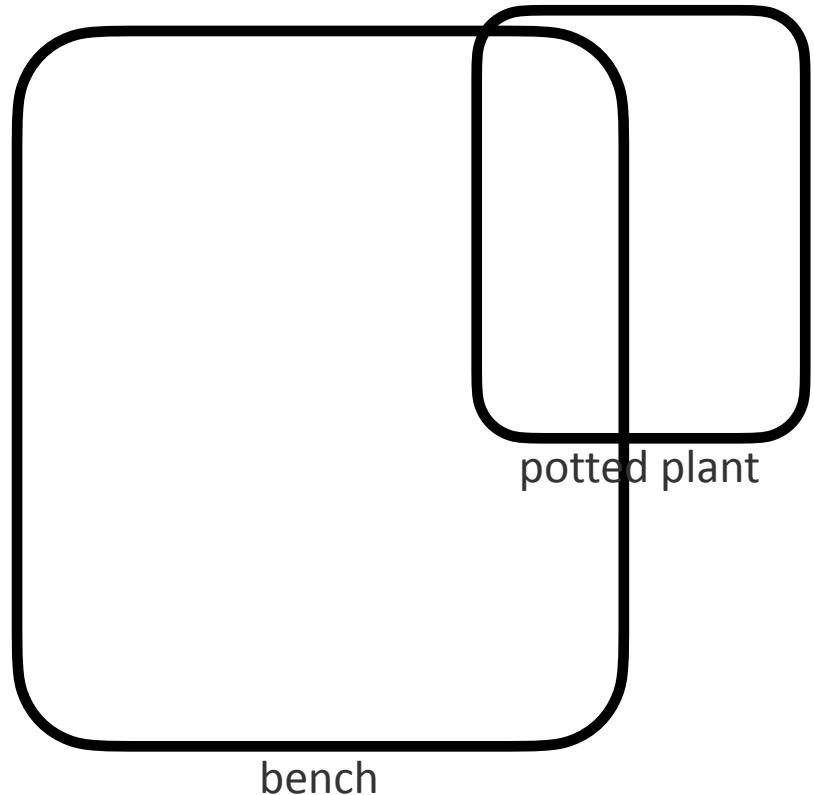


```
bbox_plant = detect(image, "potted plant")
bbox_bench = detect(image, "bench")
return bbox_plant.x > bbox_bench.x
```



Drawback: Context-Dependence

“Is the potted plant to the right of the bench?”



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bbox_plant = detect(image, "potted plant")
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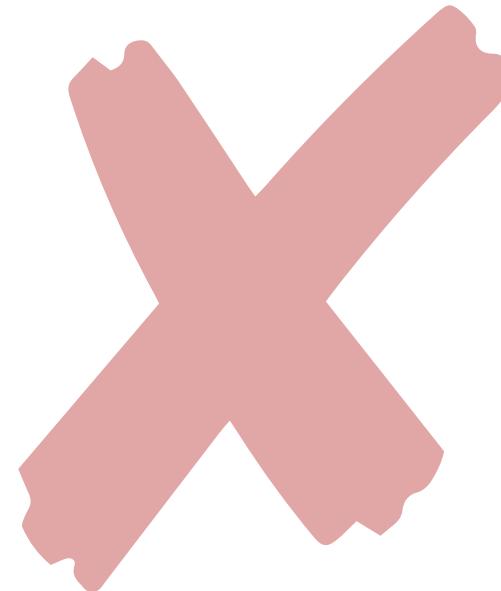


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Drawback: Context-Dependence

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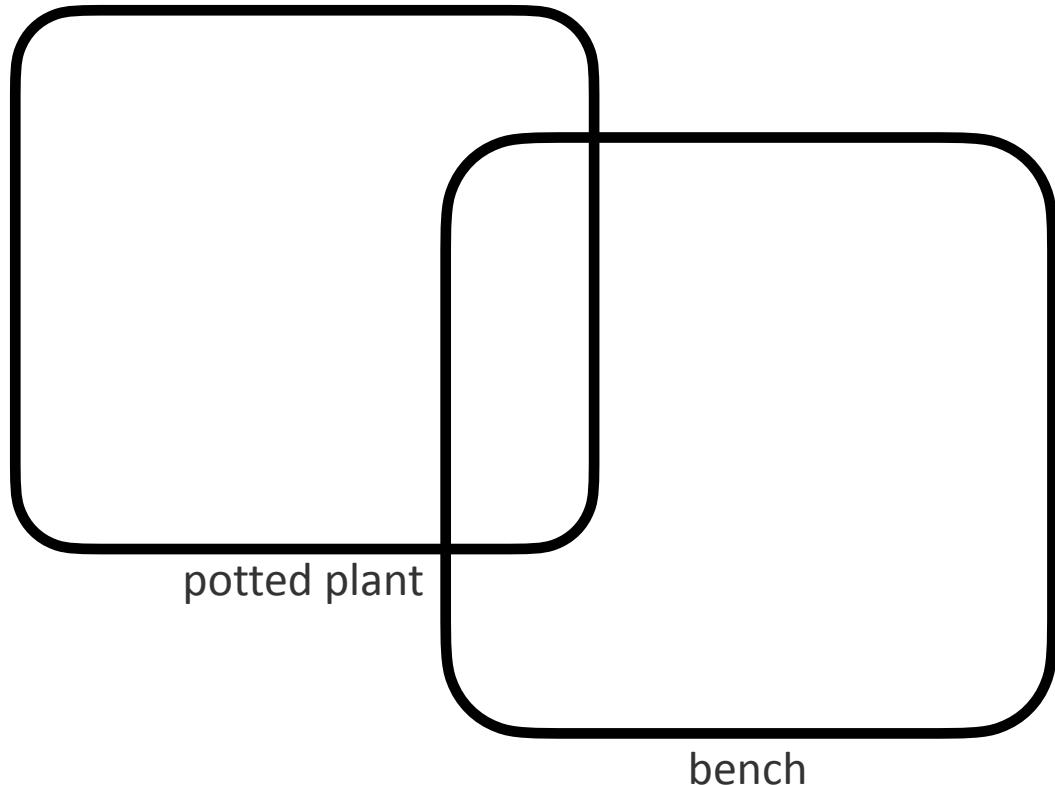
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return bbox_plant.x > bbox_bench.x
```



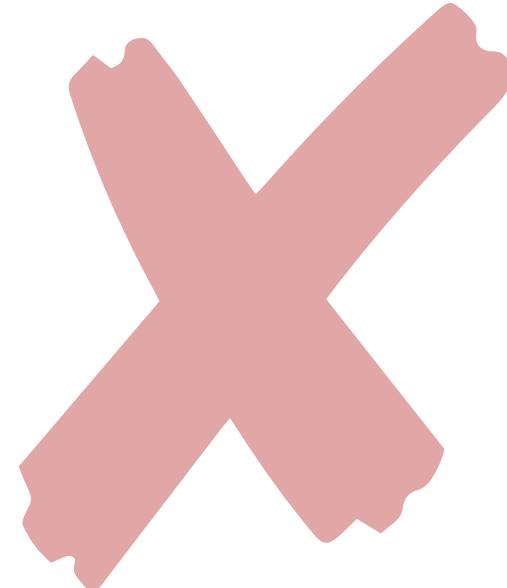


Drawback: Context-Dependence

“Is the potted plant to the right of the bench?”



```
bbox_plant = detect(image, "potted plant")
bbox_bench = detect(image, "bench")
return bbox_plant.x > bbox_bench.x
```





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