CLIP and CLIP-based Models

Learning Transferable Visual Models From Natural Language Supervision

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AIGC-Text2Image

CLIP： Bridge between Image and Text

vibrant portrait painting of Salvador Dalí with a robotic half face

a shiba inu wearing a beret and black turtleneck

a close up of a handpalm with leaves growing from it

an espresso machine that makes coffee from human souls, artstation

panda mad scientist mixing sparkling chemicals, artstation

a corgi's head depicted as an explosion of a nebula

From DALLE-2

OUTLINE

- Contrastive Language-Image Pre-training (CLIP)
- Visual Concepts in CLIP
- CLIP-based models for downstream tasks
- Limitations of current Multi-Modal Pretraining

Contrastive Language-Image Pre-training(CLIP)

- Natural language Supervision
- 400M Image text pairs
- Zero-shot Capability

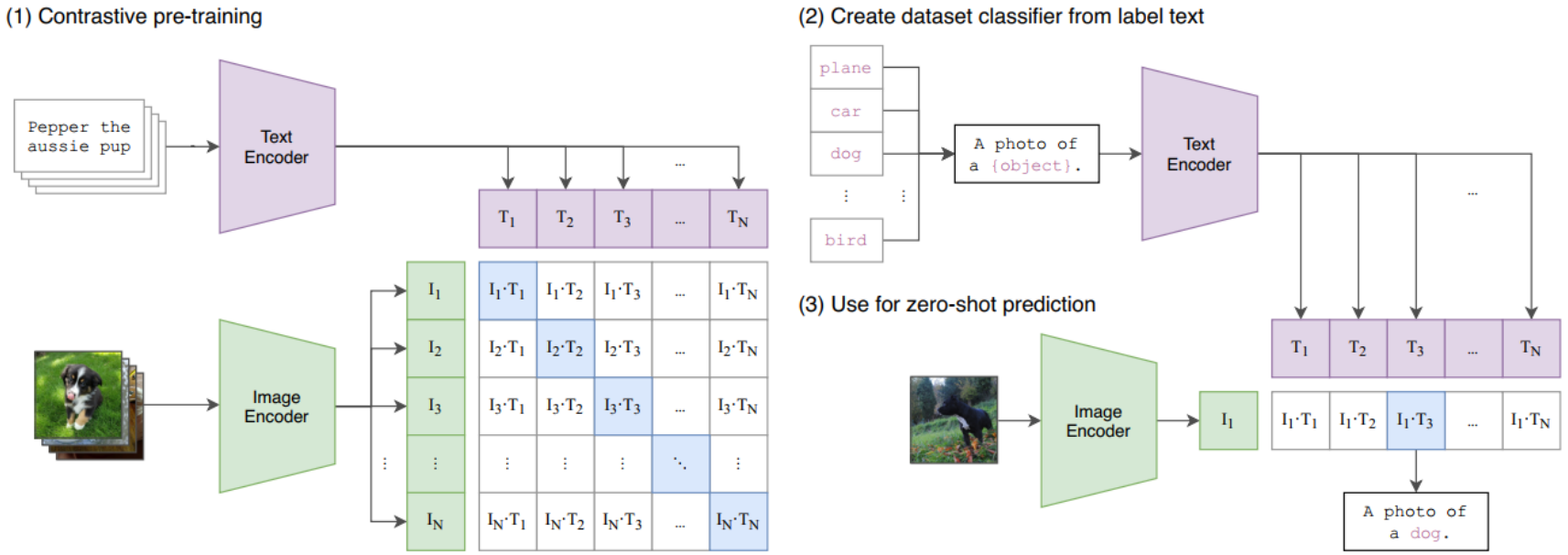
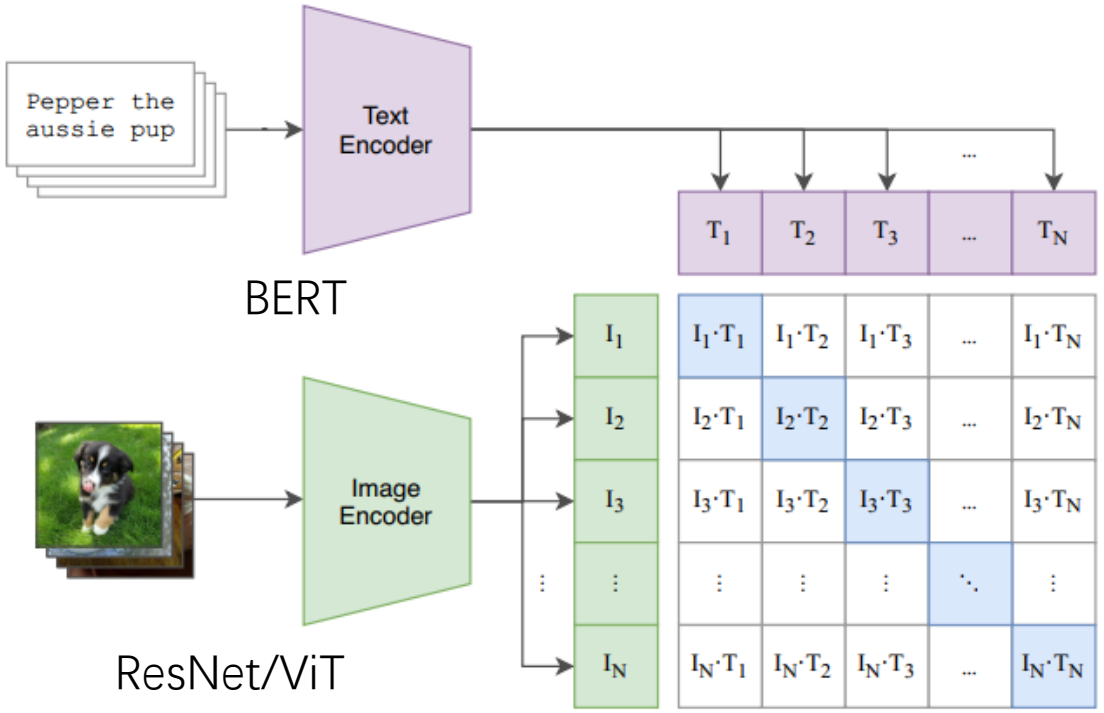


Figure 1. Summary of our approach. While standard image models jointly train an image feature extractor and a linear classifier to predict some label, CLIP jointly trains an image encoder and a text encoder to predict the correct pairings of a batch of (image, text) training examples. At test time the learned text encoder synthesizes a zero-shot linear classifier by embedding the names or descriptions of the target dataset's classes.

Contrastive Language-Image Pre-training(CLIP)

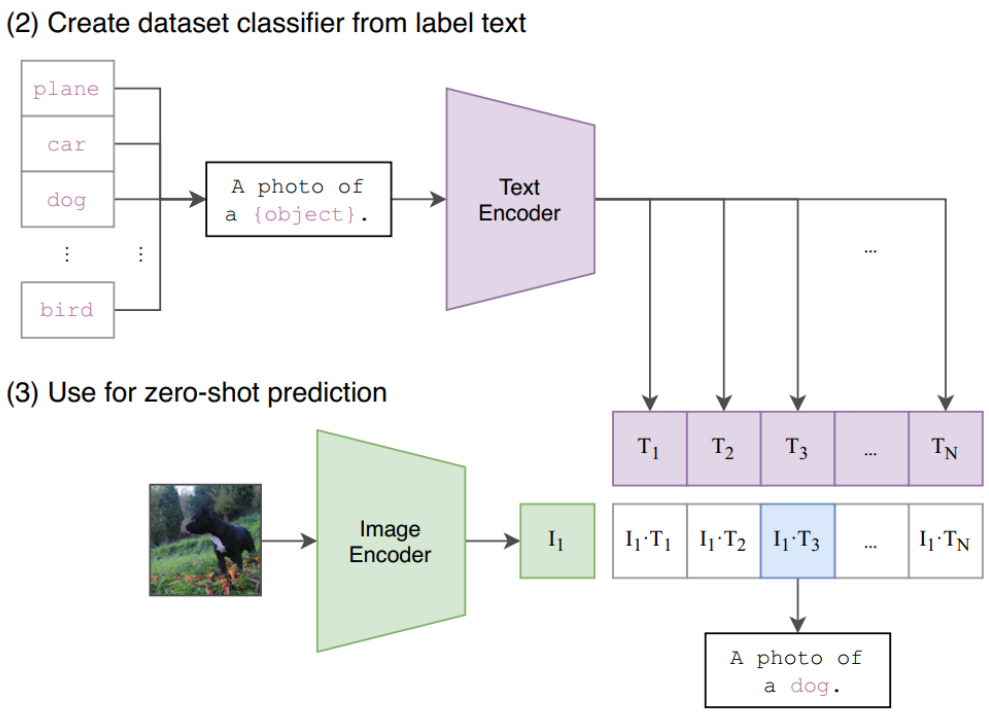
- Natural language Supervision vs Class label
  - Fine-grained label: Entity, attribute, relation



- 400M noisy Image-Text pairs
  - attempt to cover as broad a set of visual concepts as possible

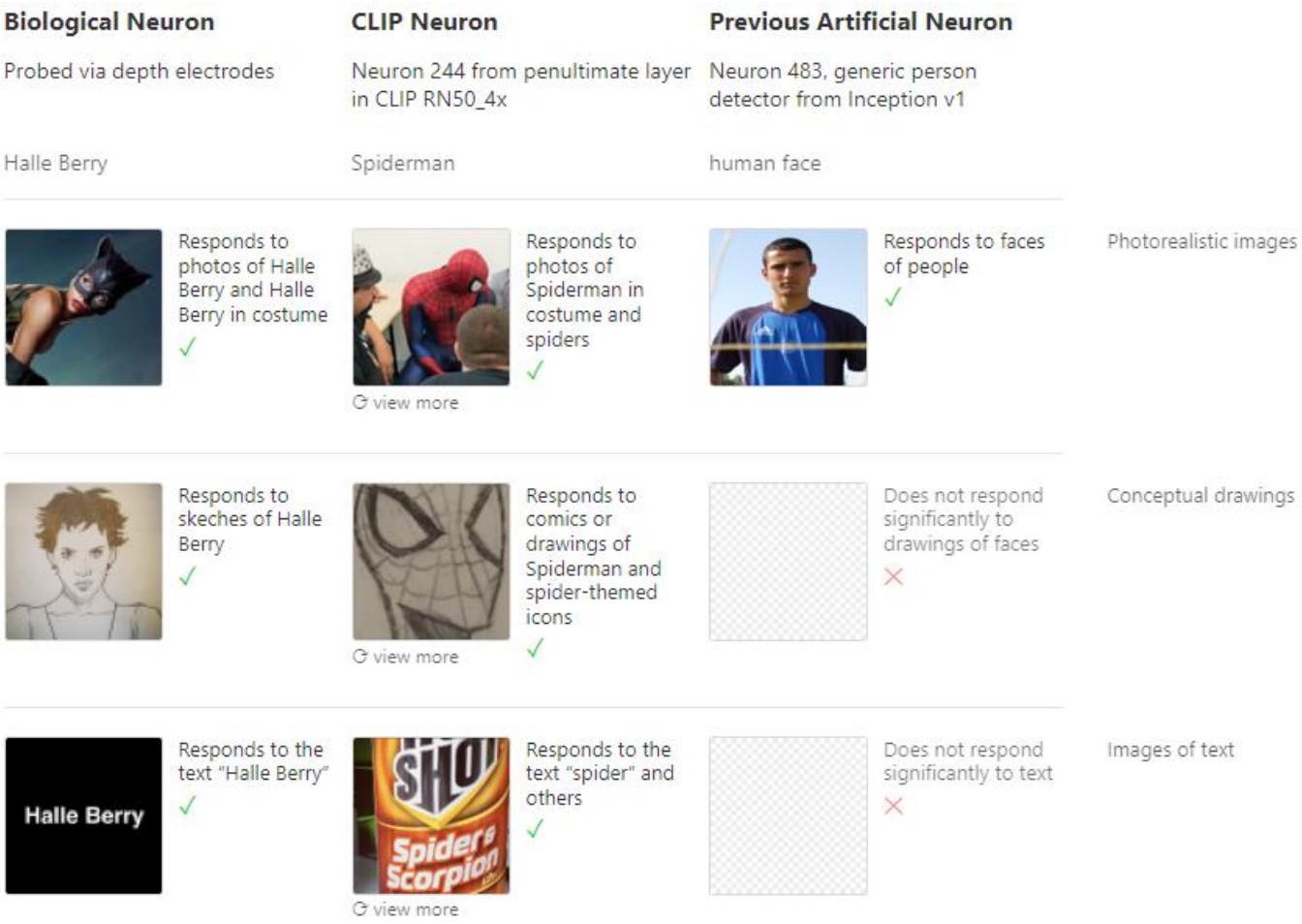
Contrastive Language-Image Pre-training(CLIP)

Zero-shot Capability



☐ Multimodal Neurons in Artificial Neural Networks (Visual Concepts in CLIP)

- Visual Concept with Multiple Visual Styles
- Neurons in CLIP Resnet layer



◘ Multimodal Neurons in Artificial Neural Networks (Visual Concepts in CLIP)

Region Neurons

Show 3 more neurons.

These neurons respond to content associated with with a geographic region, with neurons ranging in scope from entire hemispheres to individual cities. Some of these neurons partially respond to ethnicity. See Region Neurons for detailed discussion.

Person Neurons

Show 1 more neuron.

These neurons respond to content associated with with a specific person. See Person Neurons for detailed disucssion.

Emotion Neurons

Show 1 more neuron.

These neurons respond to facial expressions, words, and other content associated with an emotion or mental state. See Emotion Neurons for detailed discussion.

Religion Neurons

Show 2 more neurons.

These neurons respond to features associated with a specific religion, such as symbols, iconography, buildings, and texts.

Person Trait Neurons

Show 4 more neurons.

These neurons detect gender [10] and age, as well as facial features like mustaches. (Ethnicity tends to be represented by regional neurons.)

Art Style Neurons

Show 7 more neurons.

These neurons detect different ways in which an image might be drawn, rendered, or photographed.

Image Feature Neurons

Show 8 more neurons.

These neurons detect features that an image might contain, whether it's normal object recognition or detection of more exotic features such as watermarks or sneaky bunny ears.

Holiday Neurons

Show 2 more neurons.

These neurons recognize the names, decorations, and traditional trappings around a holiday.

Fictional Universe Neurons

Show 4 more neurons.

These neurons represent characters and concepts from within particular fictional universes.

Brand Neurons

Show 7 more neurons.

Like the neurons that recognize the identities of people, these neurons recognize brand identities.

Typographic Neurons

Show 2 more neurons.

Surprisingly, despite being able to "read" words and map them to semantic features, the model keeps a handful of more typographic features in its high-level representations. Like a child spelling out a word they don't know, we suspect these neurons help the model represent text it can't fully read.

Abstract Concept Neurons

Show 8 more neurons.

Finally, many of the neurons in the model contribute to recognizing an incredible diversity of abstract concepts that cannot be cleanly classified into the above categories.

Counting Neurons

These neurons detect duplicates of the same person or thing, and can distinguish them by their count.

Time Neurons

Show 4 more neurons.

These neurons respond to any visual information that contextualizes the image in a particular time – for some it's a season, for others it's a day or a month or a year, and for yet others it may be an entire era.

Color Neurons

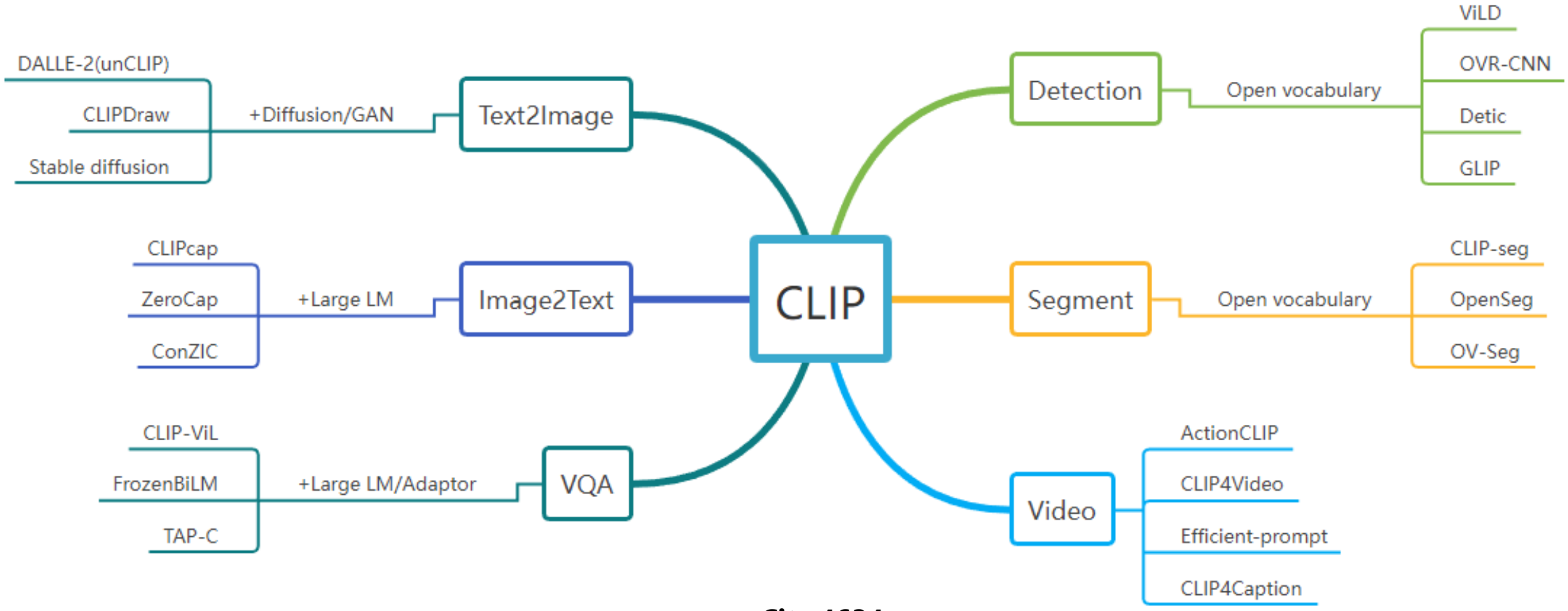
Show 2 more neurons.

These neurons detect the presence of objects in the given color.

Polysemantic Neurons

The feature visualizations and dataset examples of these neurons demonstrate some polysemanticity.

❑CLIP-based models for downstream tasks



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Open-Vocabulary Detection: ViLD

- Base categories in Training data
- Novel categories not in Training data

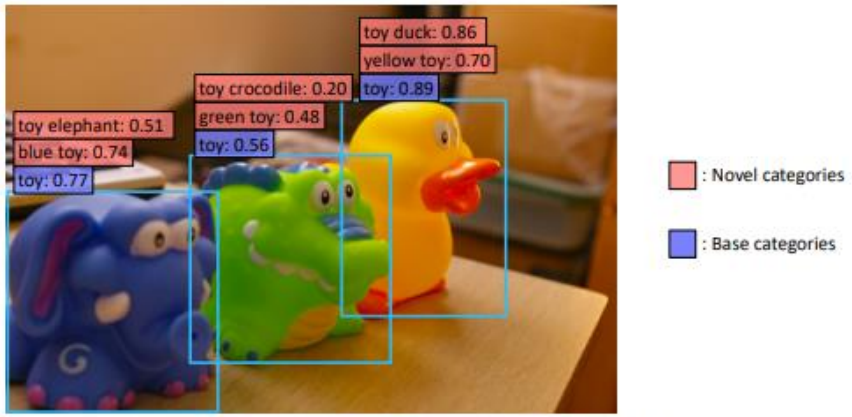
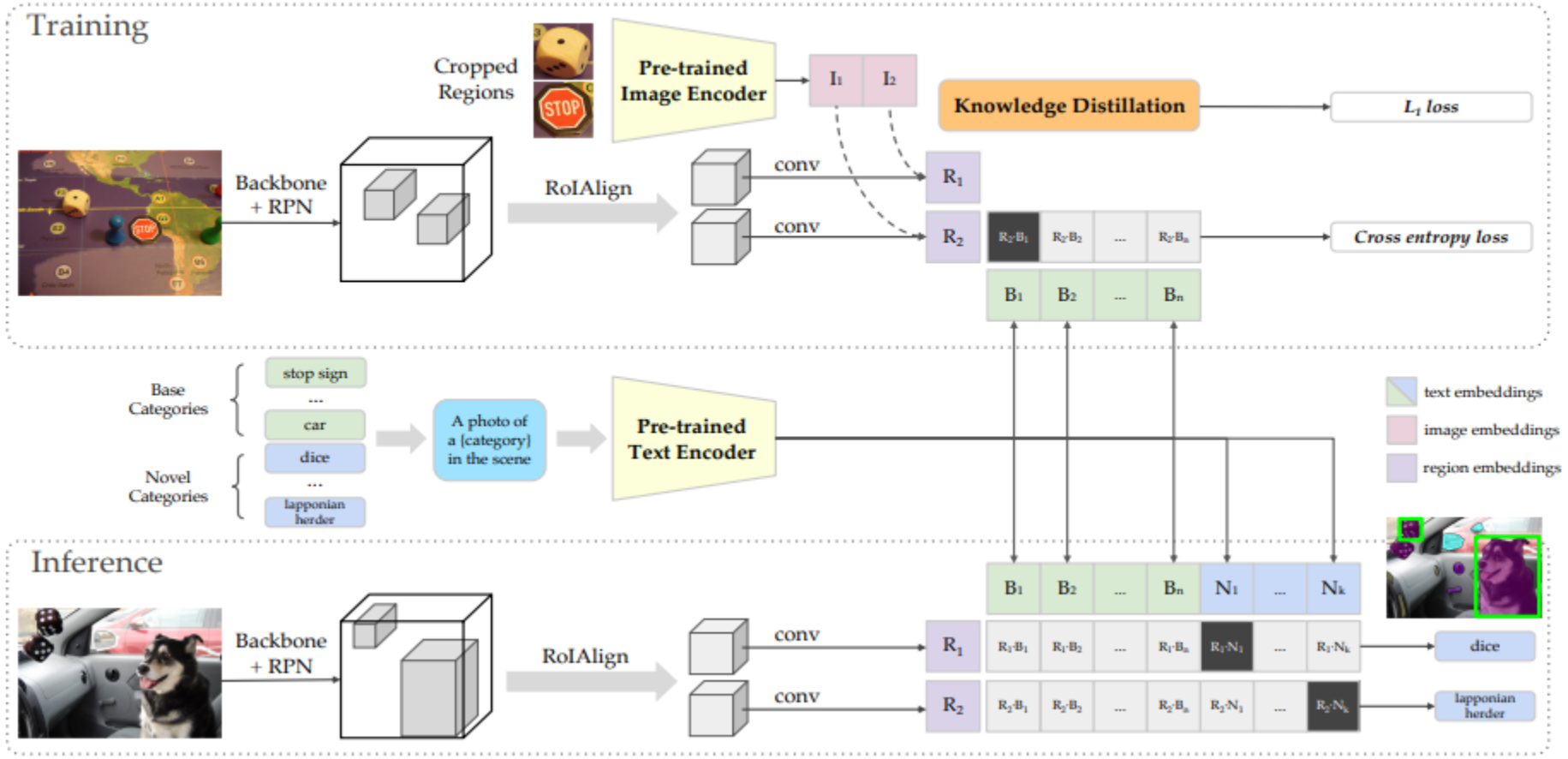


Figure 1: **An example of our open-vocabulary detector with arbitrary texts.** After training on base categories (purple), we can detect novel categories (pink) that are not present in the training data.

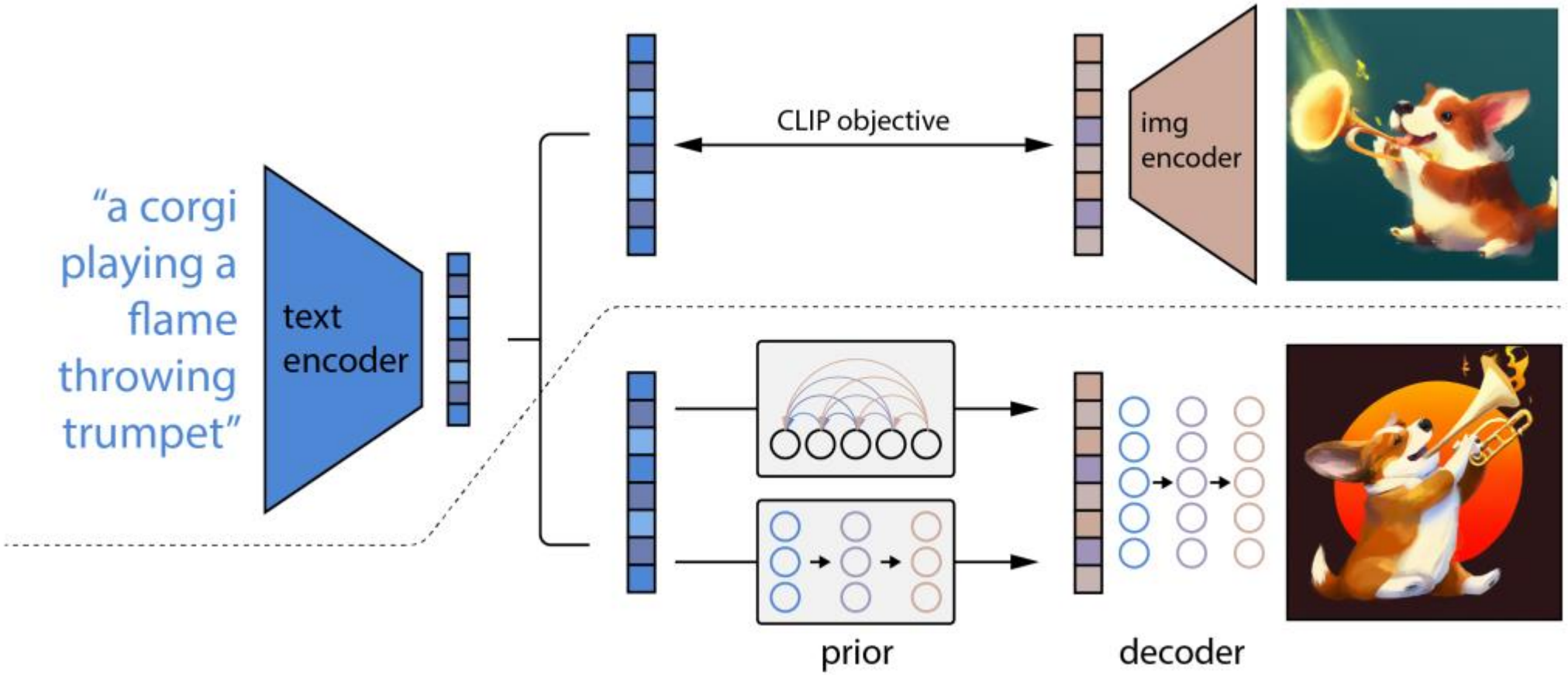
Open-Vocabulary Detection: ViLD

Framework



Text2Image: DALLE-2(unCLIP)

- Framework



Text2Image: DALLE-2(unCLIP)

an espresso machine that makes coffee from human souls, artstation

panda mad scientist mixing sparkling chemicals, artstation

a corgi's head depicted as an explosion of a nebula

a dolphin in an astronaut suit on saturn, artstation

a propaganda poster depicting a cat dressed as french emperor napoleon holding a piece of cheese

a teddy bear on a skateboard in times square

Text2Image: DALLE-2(unCLIP)

- binding wrong attributes to objects (Reconstructions)

- wrong spelling

Figure 16: Samples from unCLIP for the prompt, "A sign that says deep learning."

Limitations of current Multi-Modal Pretraining(ICLR2023 oral)

When and Why Vision-Language Models Behave like Bags-Of-Words, and What to Do About It?

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- Lack of Compositional Understanding and Order information
  - Attributes: understanding of objects' properties
  - Relation: relational understanding
  - Order: order sensitivity

☐Limitations of current Multi-Modal Pretraining(ICLR2023 oral)

Visual Genome Relation

Assessing relational understanding (23,937 test cases)

✔ *the person is riding the motorcycle*
✗ *the motorcycle is riding the person*

Visual Genome Attribution

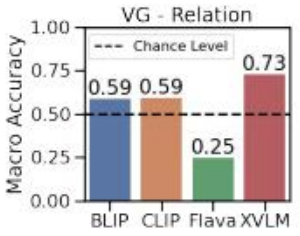
Assessing attributive understanding (28,748 test cases)

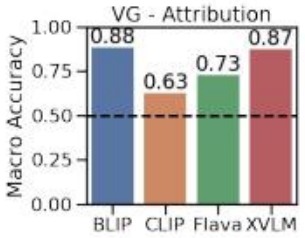
✔ *the paved road and the white house*
✗ *the white road and the paved house*

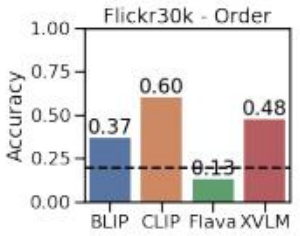
COCO Order and Flickr Order

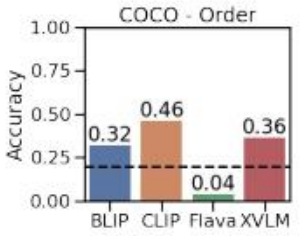
Assessing sensitivity to order (6,000 test cases)

✔ a brown cat is looking at a gray dog and sitting in a white bathtub
✗ (shuffle adjective/noun) a gray bathtub is looking at a white cat and sitting in a brown dog
✗ (shuffle all but adjective/noun) at brown cat a in looking a gray dog sitting is and a white bathtub
✗ (shuffle words within trigrams) cat brown a at is looking a gray dog in and sitting bathtub a white
✗ (shuffle trigrams) a brown cat a white bathtub is looking at a gray dog and sitting in







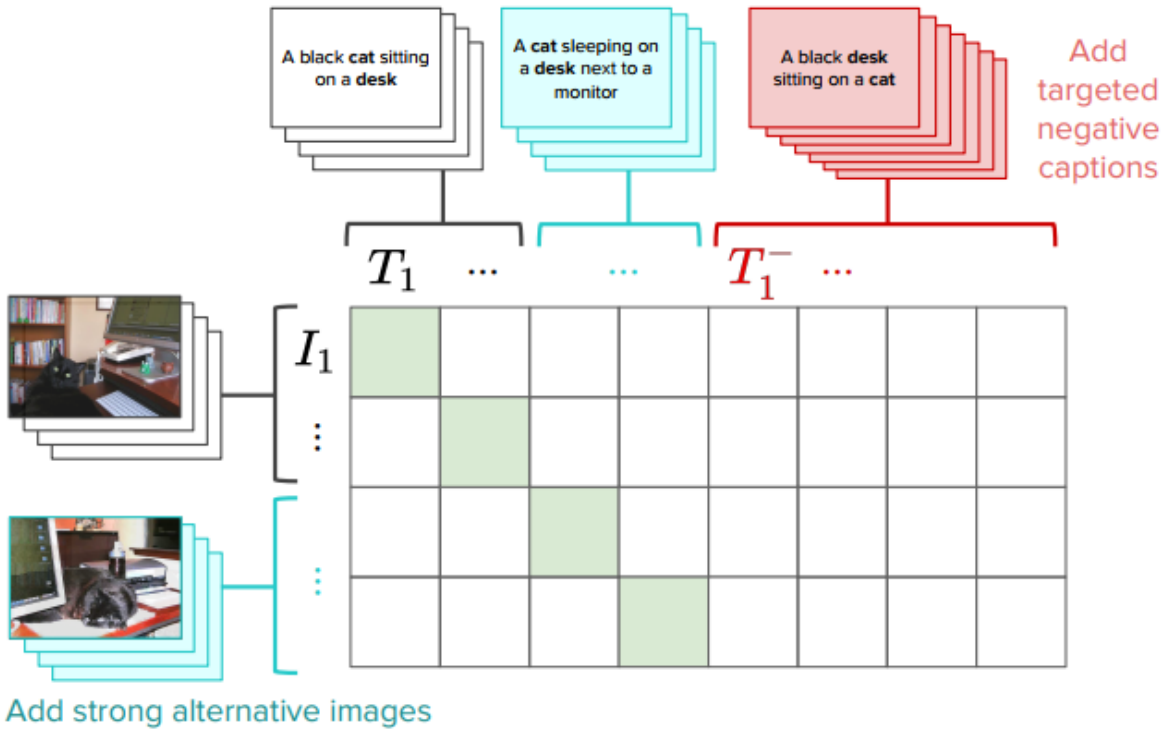


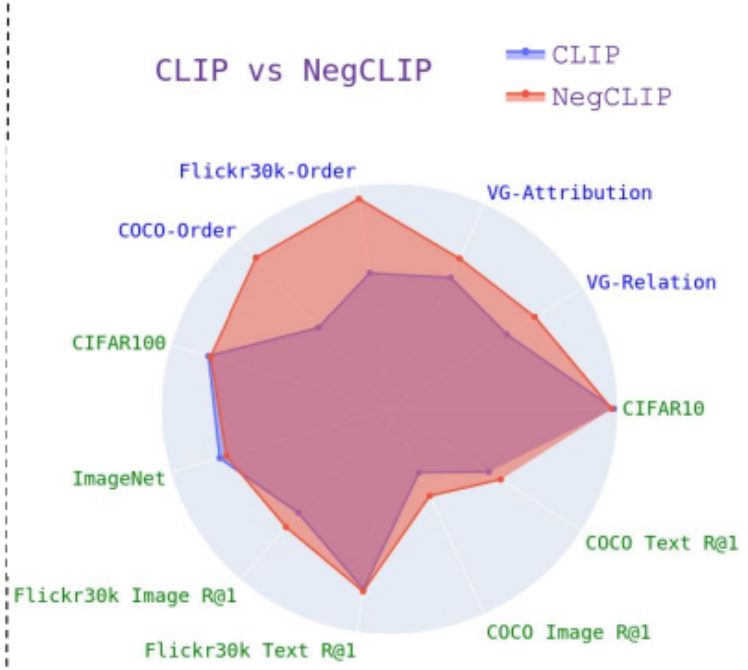
BLIP

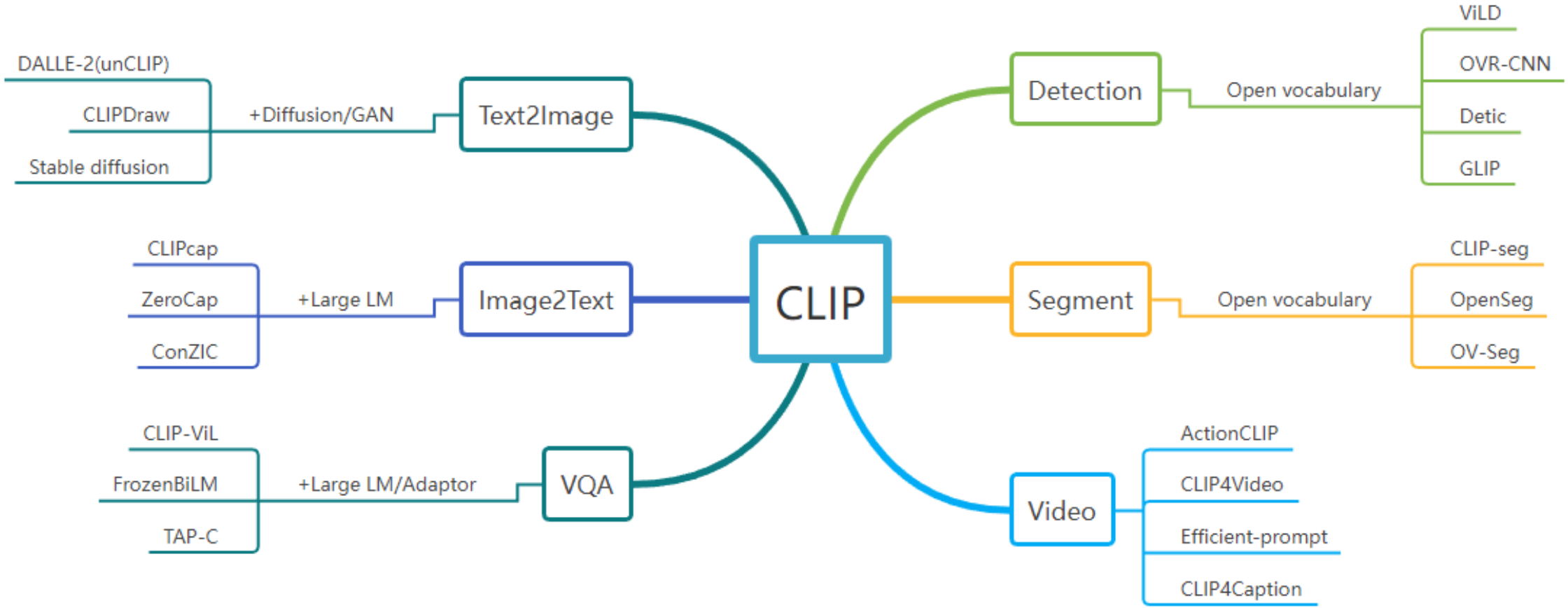
the grass is eating the horse	**81%**
the horse is eating the grass	78%

Limitation of current Multi-Modal Pretraining(ICLR2023 oral)

- Cause: shortcut of CL pretraining
  - Scheme: Compositional hard negatives






CLIP
Text2Image
+Diffusion/GAN
DALLE-2(unCLIP)
CLIPDraw
Stable diffusion
Image2Text
+Large LM
CLIPcap
ZeroCap
ConZIC
VQA
+Large LM/Adaptor
CLIP-ViL
FrozenBiLM
TAP-C
Detection
Open vocabulary
ViLD
OVR-CNN
Detic
GLIP
Segment
Open vocabulary
CLIP-seg
OpenSeg
OV-Seg
Video
ActionCLIP
CLIP4Video
Efficient-prompt
CLIP4Caption

Q&A

Thanks for your listening!