

CLIP: Connecting text and images

EECS 598

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Agenda

1. What is CLIP?
2. How does CLIP work?
3. Why CLIP matters?



“

CLIP (Contrastive Language-Image Pre-Training) is a neural network trained on a variety of **(image, text) pairs**.

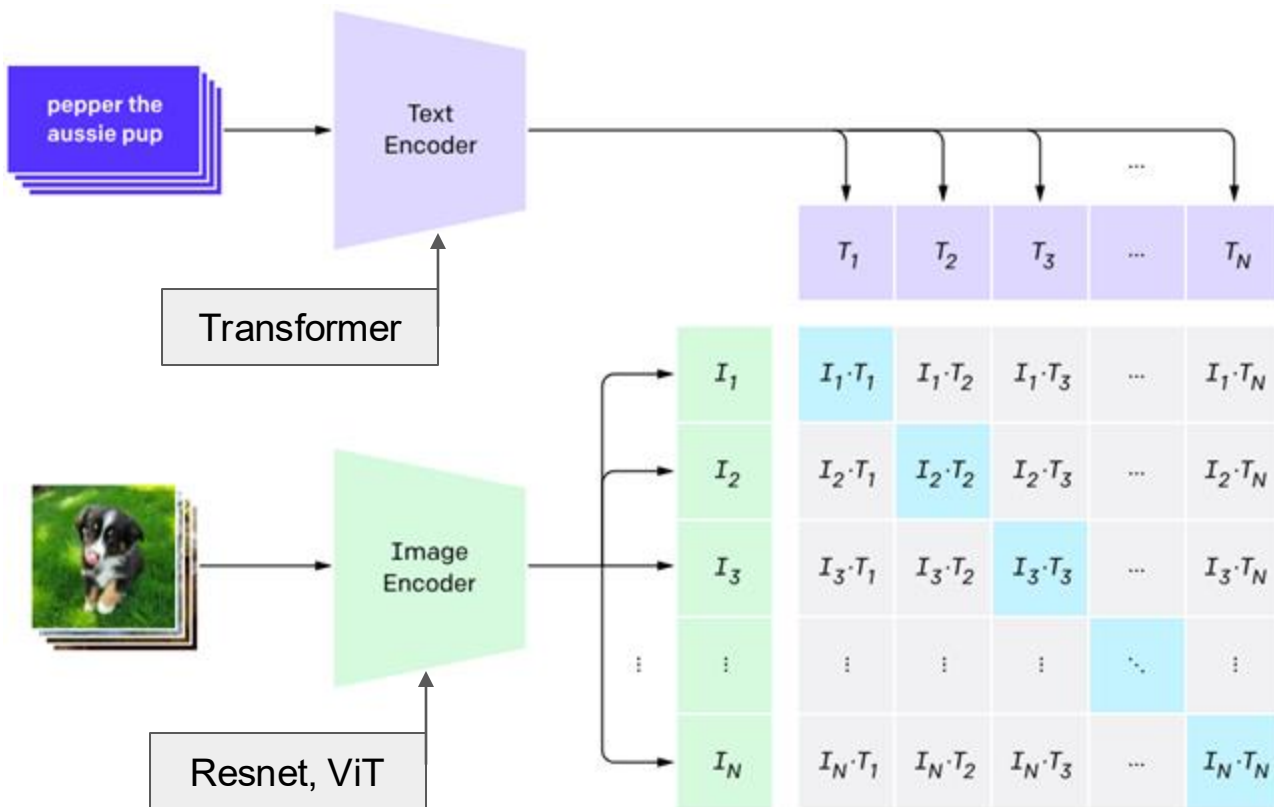
It can be instructed in natural language to **predict the most relevant text snippet** given an image, without directly optimizing for the task, similarly to the **zero-shot** capabilities of GPT-2 and 3.

”

What is CLIP?

1. **Open Source:** The model is created and open-sourced by OpenAI.
2. **Multimodal:** CLIP combines Natural Language Processing and Computer Vision.
3. **Contrastive Learning:** CLIP is trained on a huge **dataset of 400 million (image, text) pairs** collected from the internet
 - a. With Contrastive Learning, CLIP is trained to learn that similar text-image should be close in the latent space, while dissimilar ones should be far apart.
4. **Zero-shot learning** enables the generalization of unseen labels, without having explicitly trained to classify them.
 - a. For example, all ImageNet models are trained to recognize 1000 specific classes. CLIP is not bound by this limitation.

How does Contrastive Language-Image Pre-Training Work?



How does Contrastive Language-Image Pre-Training Work?

```
# 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]

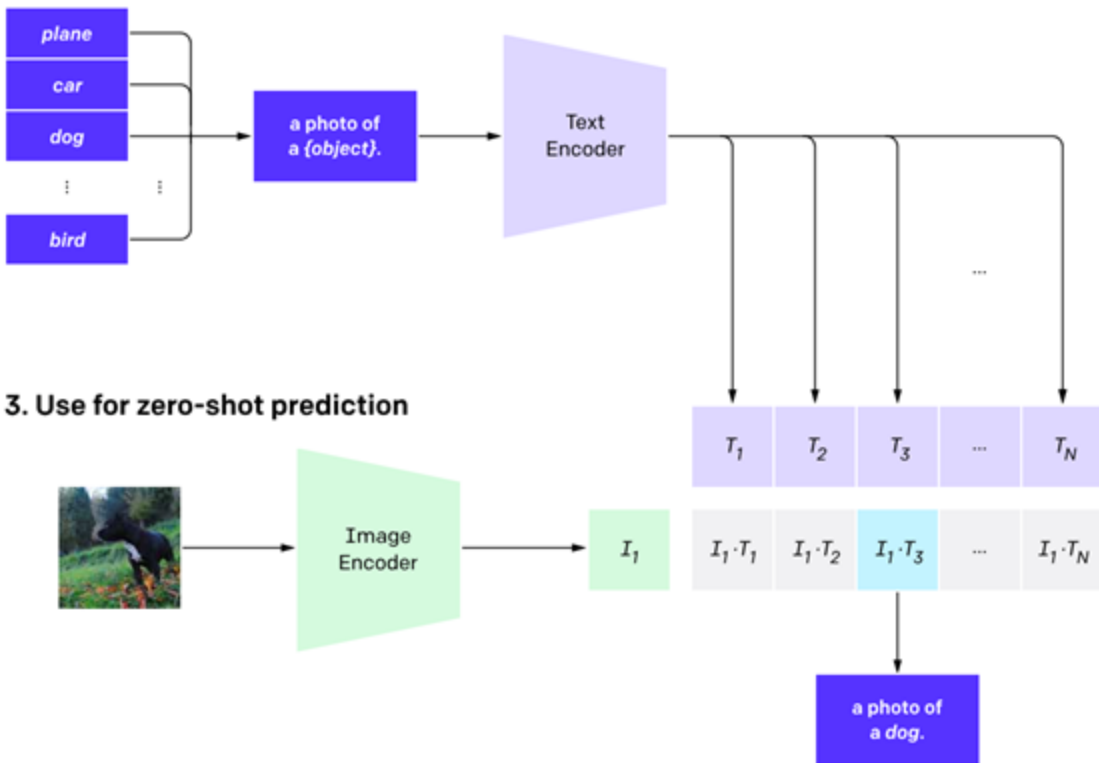
# joint multimodal embedding [n, d_e]
I_e = l2_normalize(np.dot(I_f, W_i), axis=1)
T_e = l2_normalize(np.dot(T_f, W_t), axis=1)

# 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
```

How does CLIP Predict?

2. Create dataset classifier from label text



Results of CLIP

Food101

guacamole (90.1%) Ranked 1 out of 101 labels



✓ a photo of **guacamole**, a type of food.

X a photo of **ceviche**, a type of food.

X a photo of **edamame**, a type of food.

X a photo of **tuna tartare**, a type of food.

X a photo of **hummus**, a type of food.

SUN397

television studio (90.2%) Ranked 1 out of 397 labels



✓ a photo of a **television studio**.

X a photo of a **podium indoor**.

X a photo of a **conference room**.

X a photo of a **lecture room**.

X a photo of a **control room**.

Youtube-BB

airplane, person (89.0%) Ranked 1 out of 23 labels



✓ a photo of a **airplane**.

X a photo of a **bird**.

X a photo of a **bear**.

X a photo of a **giraffe**.

X a photo of a **car**.

EuroSAT

annual crop land (46.5%) Ranked 4 out of 10 labels



X a centered satellite photo of **permanent crop land**.

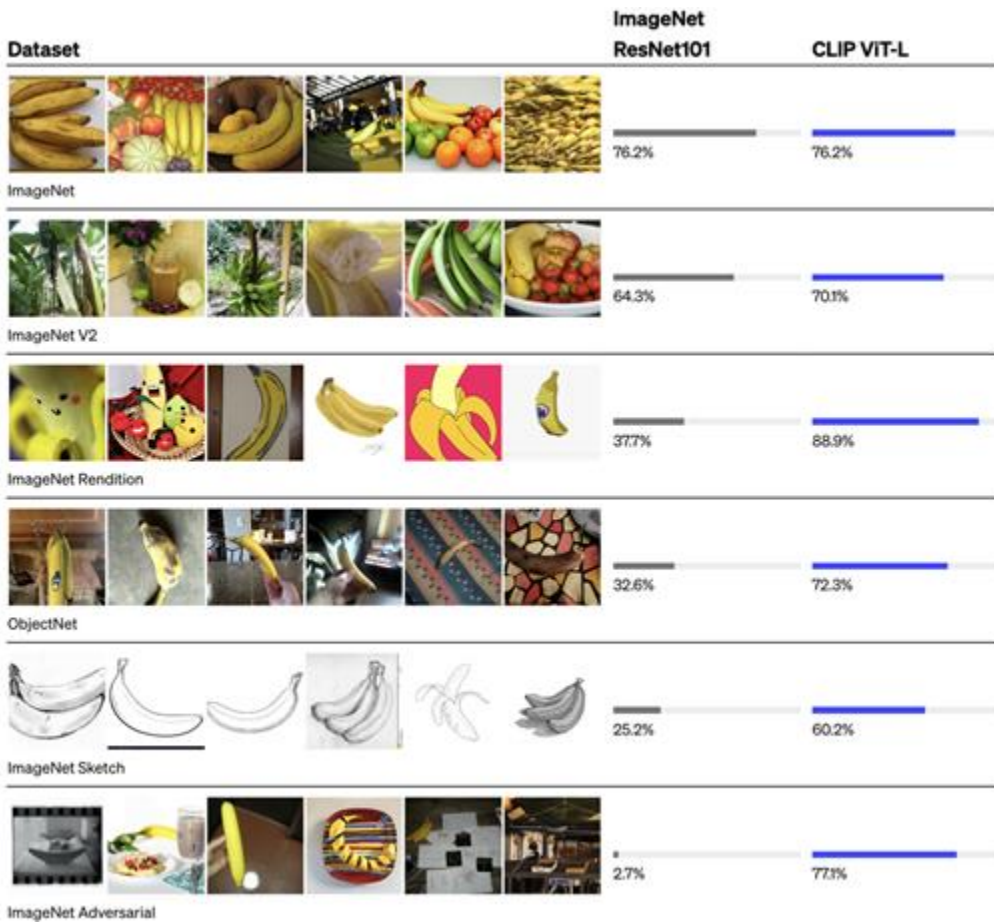
X a centered satellite photo of **pasture land**.

X a centered satellite photo of **highway or road**.

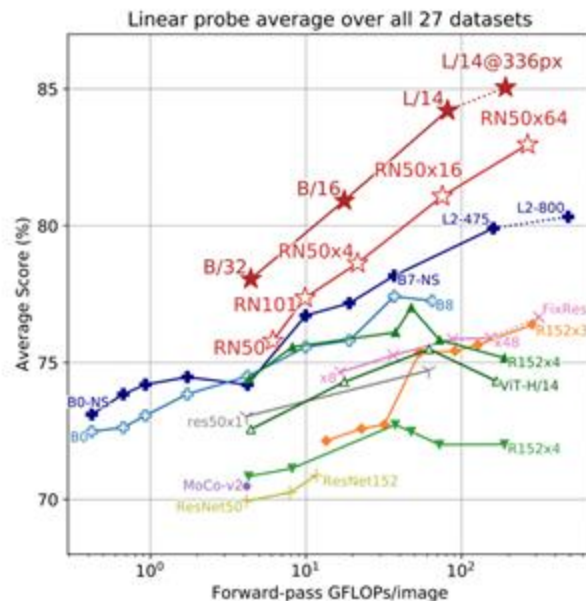
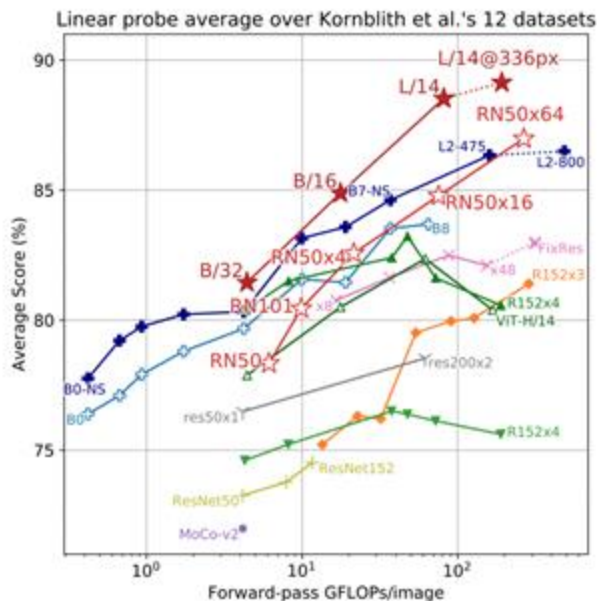
✓ a centered satellite photo of **annual crop land**.

X a centered satellite photo of **brushland or shrubland**.

Results of CLIP



Experiment Results of CLIP



Recap: Why does CLIP Matter?

1. Bridge Visual and Textual Understanding
2. Zero-Shot Learning Capabilities
3. Robustness Against Adversarial Attacks
4. Training data efficiency

Training Resources for CLIP

1. Training data size: 400,000,000 image-text pairs.
2. Training time: 30 GPU days across 592 V100 GPUs.
3. Training cost: \$1,000,000 on AWS on-demand instances

Challenges and Limitation of CLIP

1. Computation-Intensive
2. Struggles on more abstract or systematic tasks
 - a. Count the number of objects in an image
 - b. Predict how close the nearest car is in a photo.
3. CLIP also still has poor generalization to images not covered in its pre-training dataset.
4. Sensitive to wording or phrasing

Follow-up Works of CLIP

1. Object detection
2. Image segmentation
3. Motion detection
4. Video/Image search
5. Multimodality
6. Image generation
7. ...

Q&A