CLIP

Contrastive Language Image Pre-training

Lecture-4

CAP6412, Spring 2025

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Learning Transferable Visual Models from Natural Language Supervision

Alec Radford JongWook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, lya Sutskever

ICML-2021; 27,376 Citations

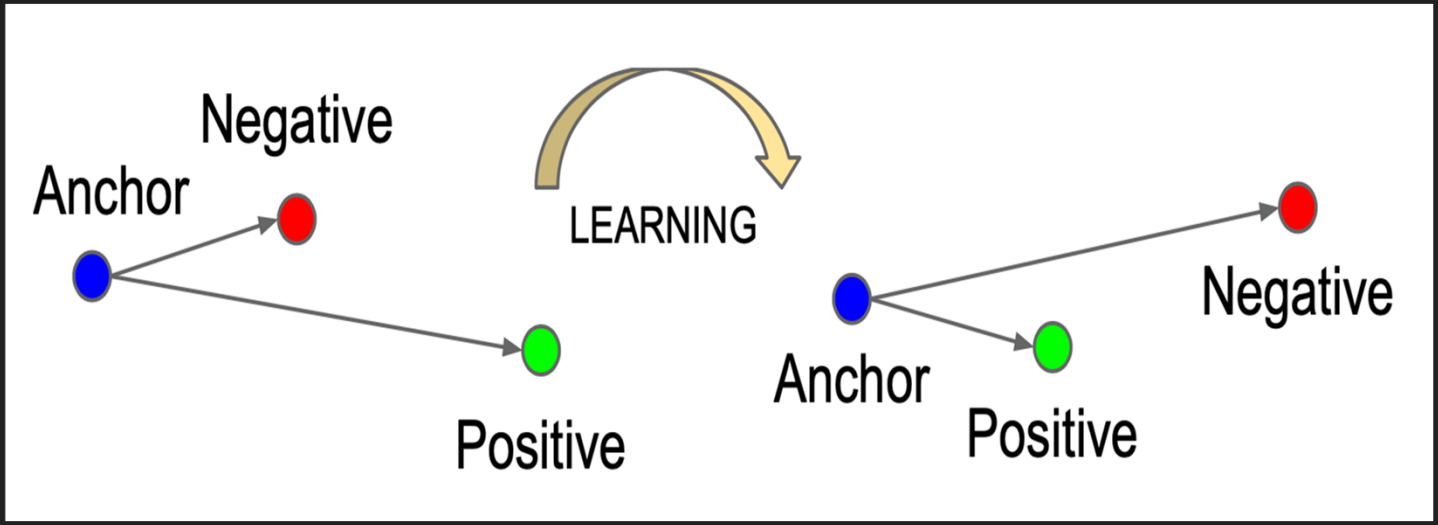
Presented by: Moazam Soomro, Fatemah Najafali, Alec Kerrigan, and Connor Malley

CAP6412;
https://www.youtube.com/watch?v=t5MPdf8NG1g

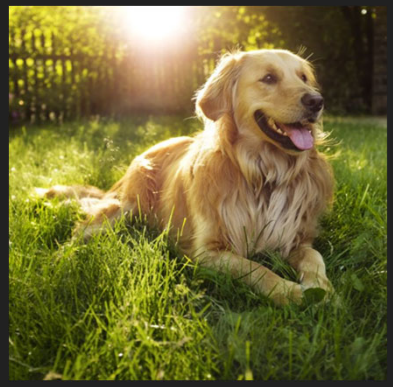
Contrastive Language Image Pre-training (CLIP)

- Mechanism for natural language supervision
- Pair an image with it’s caption using contrastive learning
- Beats fully supervised learning baseline on many datasets
- Can be used as a zero-shot classifier

What is Contrastive Learning?



Contrastive Learning Objective - similar (image, text) pair



Input Image

$\vec{H}_i$

Image Representation

A dog lying in grass

Input Text

$\vec{H}_t$

Text Representation

$$maximize(\frac{\vec{H}_i \cdot \vec{H}_t}{\|\vec{H}_i\| \times \|\vec{H}_t\|})$$

Contrastive Learning Objective - dissimilar (image, text) pair



Input Image

$\vec{H}_i$

Image Representation

A dog lying in grass

Input Text

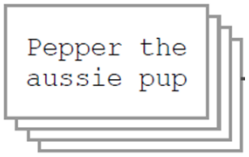
$\vec{H}_t$

Text Representation

$$minimize(\frac{\vec{H}_i \cdot \vec{H}_t}{\|\vec{H}_i\| \times \|\vec{H}_t\|})$$

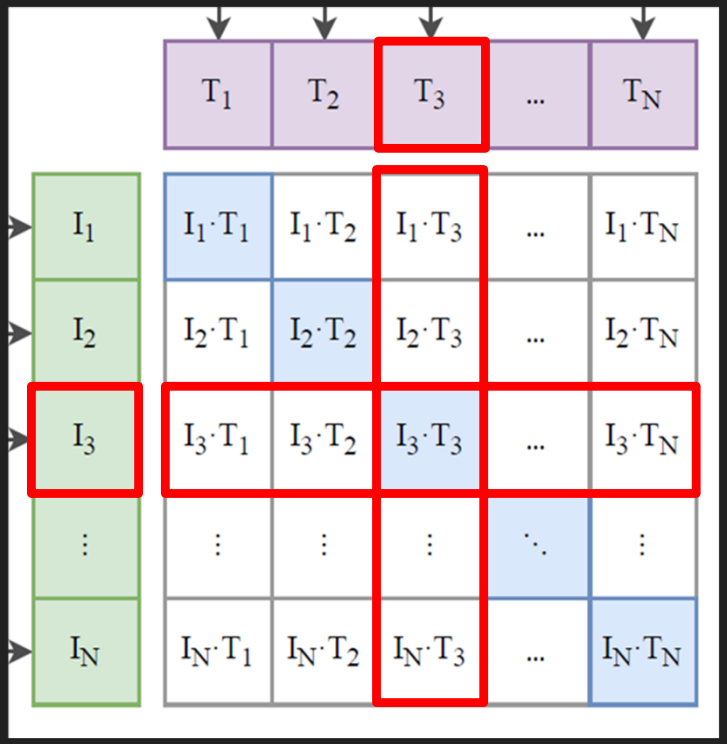
CLIP Pre-training

(1) Contrastive pre-training





Computing Loss



m_i = one-hot encoded label vector for the i-th image sample

y_i^m = cosine similarities vector for i-th image sample

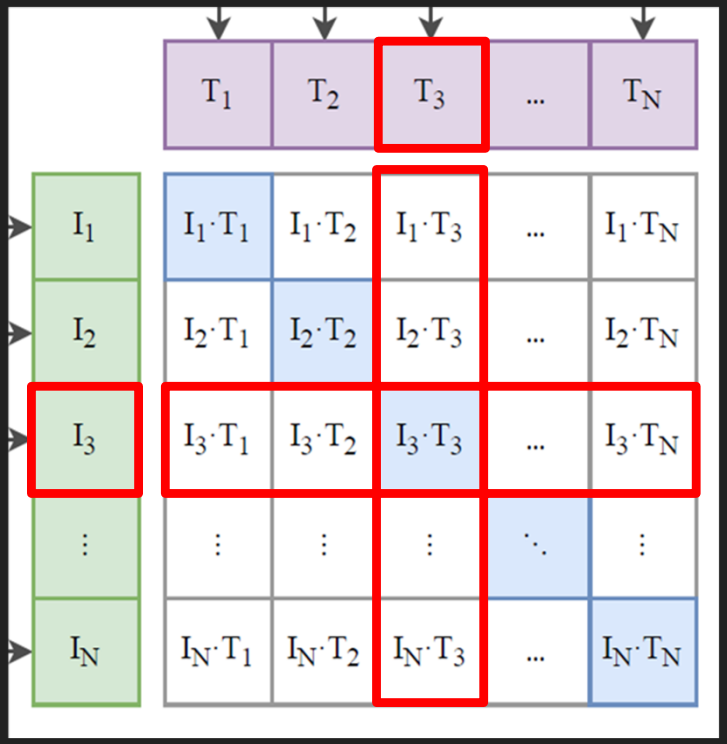
t_i =one-hot encoded label for the i-th text sample

y_i^t = cosine similarities vector for i-th text sample

ϕ = cross entropy loss

- Cross Entropy: $C(P) = -\Sigma_i P(i) \log Q(i)$

Computing Loss



m_i = one-hot encoded label vector for the i-th image sample

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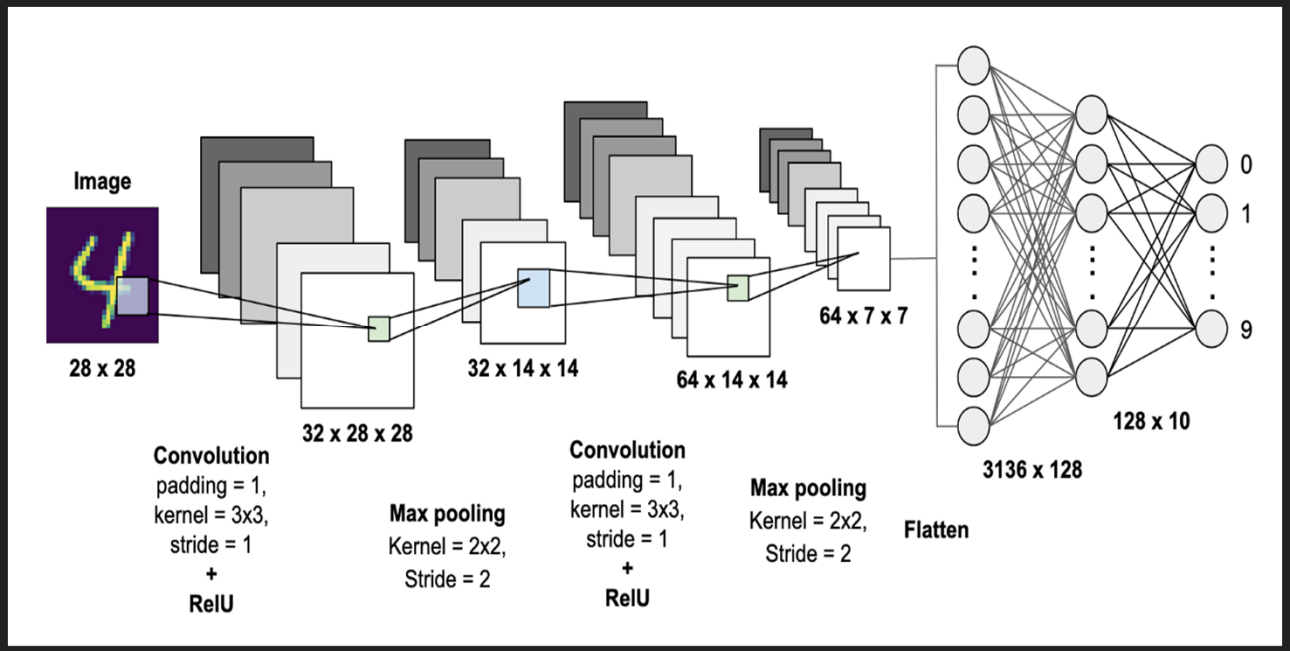
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- Cross Entropy: $C(P) = -\Sigma_i P(i) \log Q(i)$

$$\mathcal{L}_m = \frac{\sum_{i=1}^{N} \phi(y_i^m, m_i)}{N} \quad \mathcal{L}_t = \frac{\sum_{i=1}^{N} \phi(y_i^t, t_i)}{N}$$

$$\mathcal{L} = \frac{\mathcal{L}_m + \mathcal{L}_t}{2}$$

Supervised Classification



Supervised Learning vs Zero Shot Learning

SUPERVISED LEARNING

- Labeled data
- Training phase
- Final prediction on labeled data

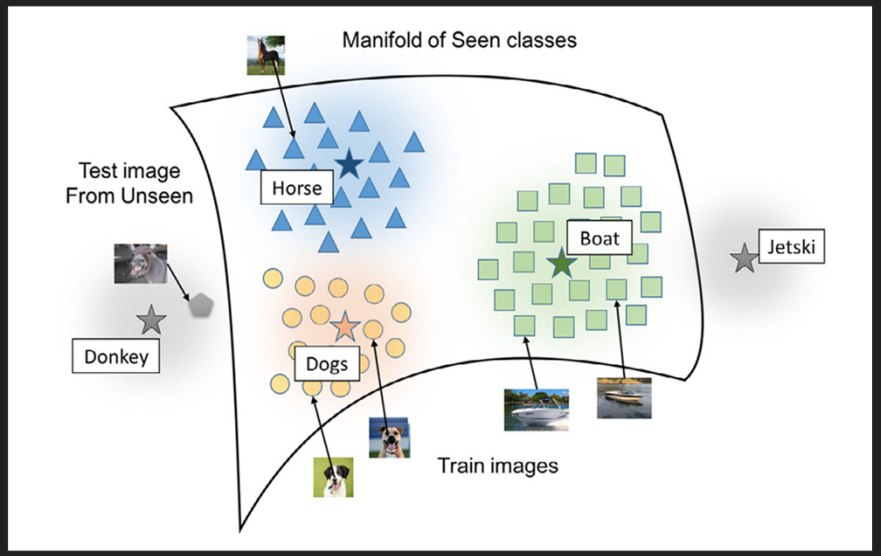
ZERO SHOT LEARNING

- Data can be labeled/unlabeled
- No training
- Accuracy on the final results

Motivation

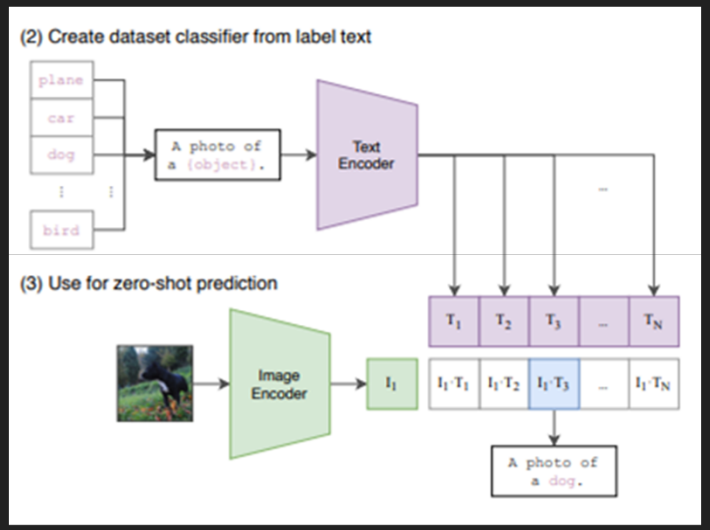
- Image classification models are limited:
  - Fixed number of labels
  - Generalization
- CLIP overcomes these limitations.

What is Zero-Shot Learning?



- To train on one dataset and generalizing on unseen categories.

CLIP for Zero-Shot Image Classificaiton



WebImageText Dataset

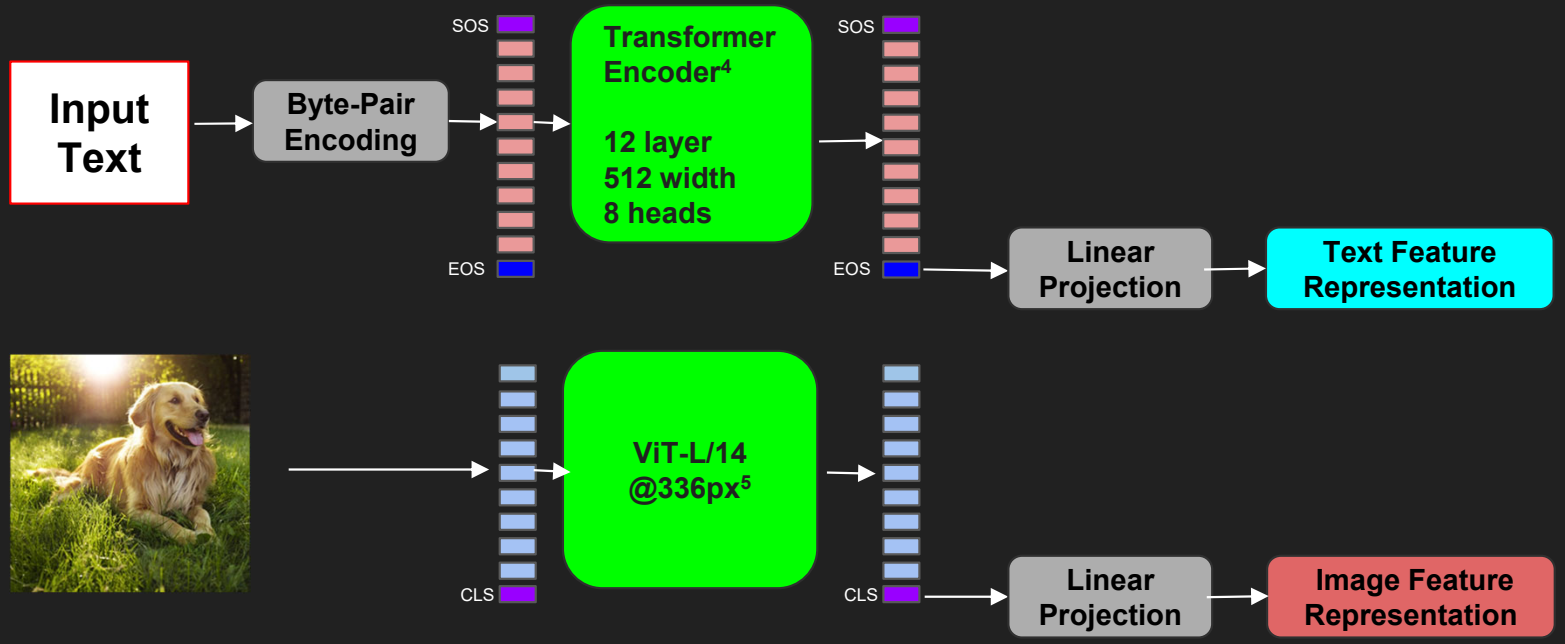
- Motivation for using natural language is the vast amounts of data
- Previous datasets did not have enough natural language descriptions (YFCC100M)
- Authors searched for (image, text) pairs which contained one of 500,000 text queries
- Used for pre-training CLIP

WebImageText (WIT)

400M (image,text) pairs

Up to 20,000 pairs per query

CLIP Architecture



* Authors also tested many other ResNet/ViT variants, but found this ViT to perform the best

Some CLIP details

Training

- Trained on 400M image-text pairs from the internet
- Batch size of 32,768
- 32 epochs over the dataset
- Cosine learning rate decay

Architecture

- ResNet-based orViT-based image encoder
- Transformer-based text encoder

Testing

- Linear Probe

- Zero-shot Prediction

Linear Probe CLIP

- Train a linear classifier on another dataset using CLIP features

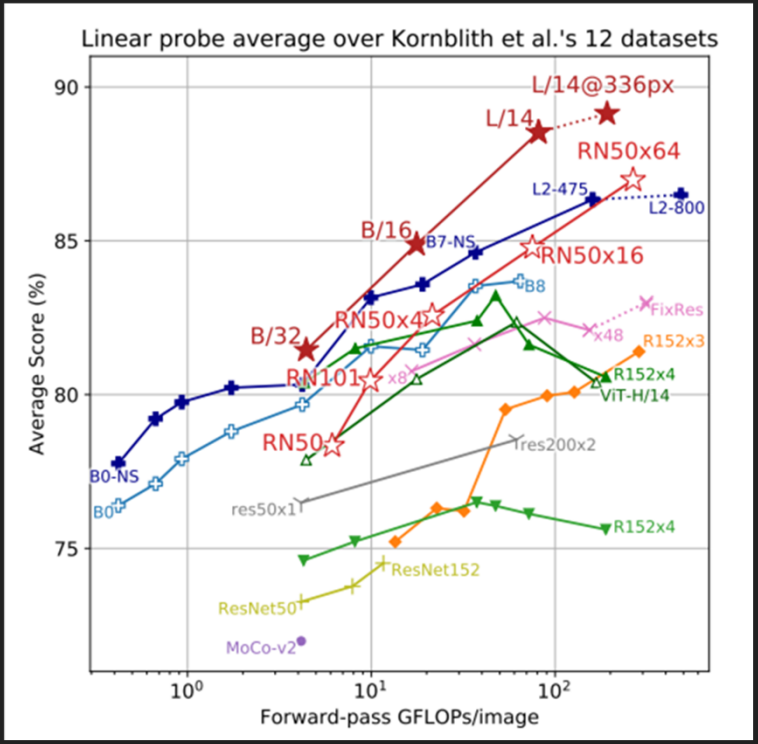
Kornblith et al.'s 12 datasets

Dataset	Classes	Train size	Test size	Evaluation metric
Food-101	102	75,750	25,250	accuracy
CIFAR-10	10	50,000	10,000	accuracy
CIFAR-100	100	50,000	10,000	accuracy
Birdsnap	500	42,283	2,149	accuracy
SUN397	397	19,850	19,850	accuracy
Stanford Cars	196	8,144	8,041	accuracy
FGVC Aircraft	100	6,667	3,333	mean per class
Pascal VOC 2007 Classification	20	5,011	4,952	11-point mAP
Describable Textures	47	3,760	1,880	accuracy
Oxford-IIIT Pets	37	3,680	3,669	mean per class
Caltech-101	102	3,060	6,085	mean-per-class
Oxford Flowers 102	102	2,040	6,149	mean per class

Extended 27 Datasets

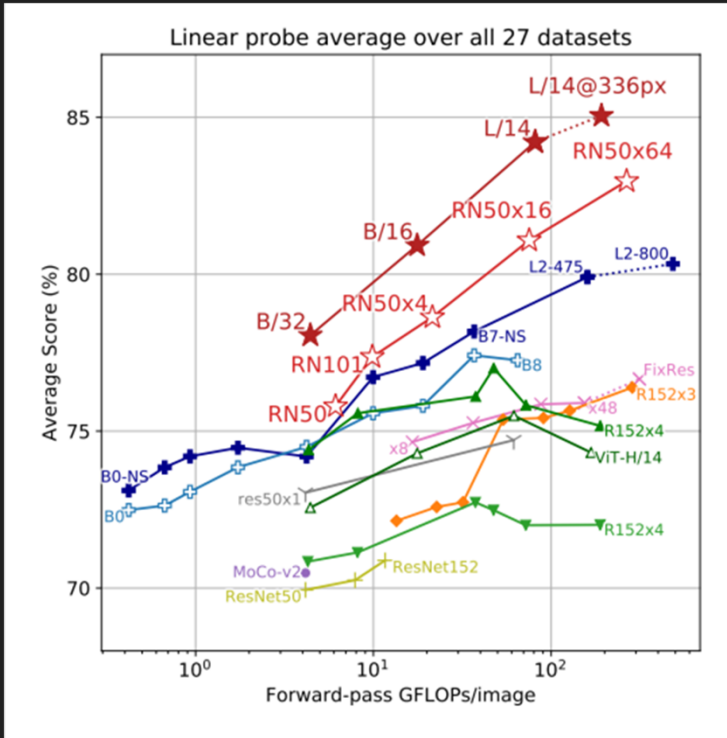
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MNIST	10	60,000	10,000	accuracy
Facial Emotion Recognition 2013	8	32,140	3,574	accuracy
STL-10	10	1000	8000	accuracy
EuroSAT	10	10,000	5,000	accuracy
RESISC45	45	3,150	25,200	accuracy
GTSRB	43	26,640	12,630	accuracy
KITTI	4	6,770	711	accuracy
Country211	211	43,200	21,100	accuracy
PatchCamelyon	2	294,912	32,768	accuracy
UCF101	101	9,537	1,794	accuracy
Kinetics700	700	494,801	31,669	mean(top1, top5)
CLEVR Counts	8	2,000	500	accuracy
Hateful Memes	2	8,500	500	ROC AUC
Rendered SST2	2	7,792	1,821	accuracy
ImageNet	1000	1,281,167	50,000	accuracy

Results - Efficiency - Kornblith



- Kornblith 12 dataset evaluation suite, standard for most works
- CLIP's ResNet based model underperforms EfficientNet
- ViT based CLIP outperforms everything

Results - Efficiency - Extended

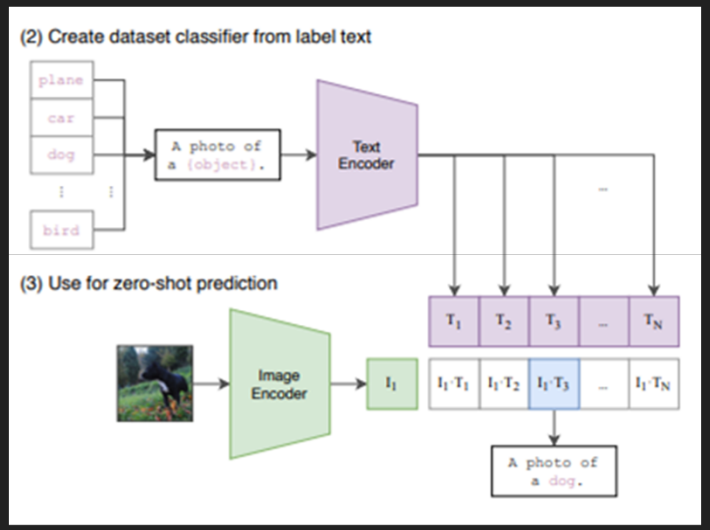


- On the extended testing suite, both CLIP versions outperform all other models
- Performance gap increases with GFLOPS

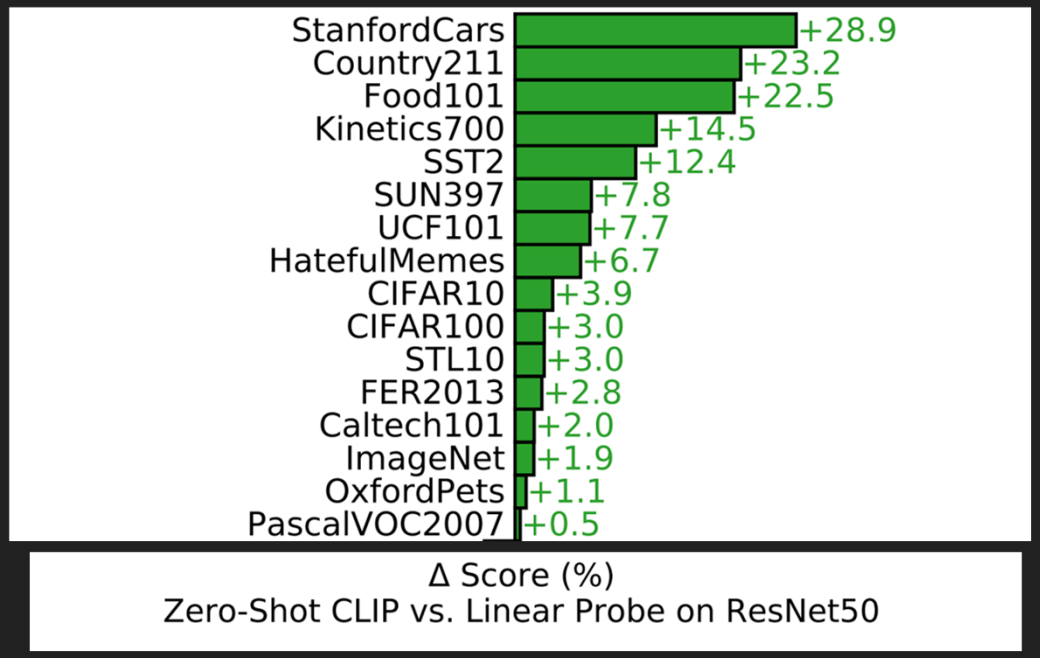
CLIP-ViT
CLIP-ResNet
EfficientNet-NoisyStudent
EfficientNet
Instagram-pretrained
SimCLRv2
BYOL
MoCo
ViT (ImageNet-21k)
BiT-M
BiT-S
ResNet

Zero-Shot

Contrastive Language Image Pre-training (CLIP)

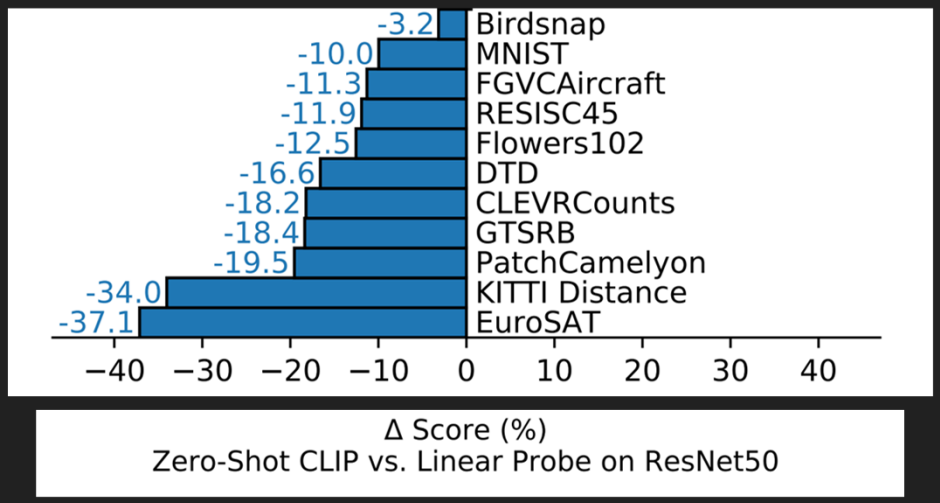


Results - Accuracy



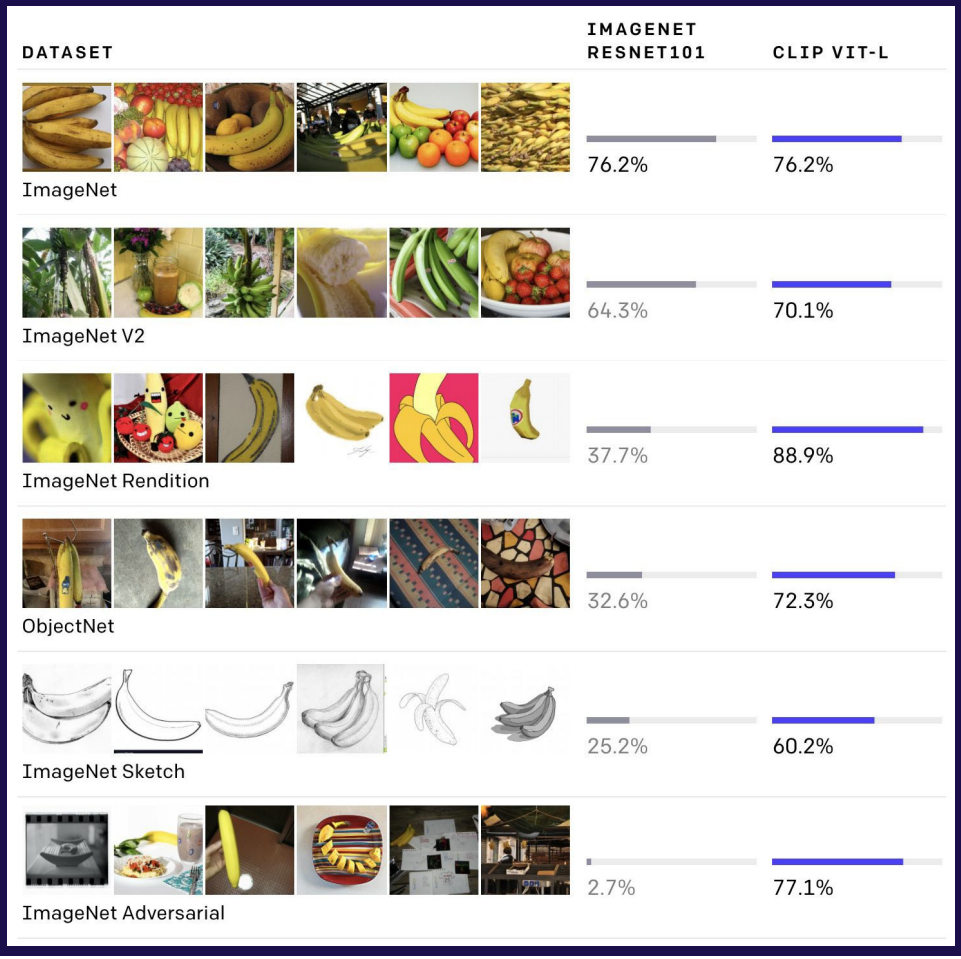
- Zero-shot CLIP using ResNet50 backbone is compared to off the shelf ResNet50
- CLIP outperforms on a wide variety of popular datasets
- For video, a single frame was sampled

Results - Accuracy

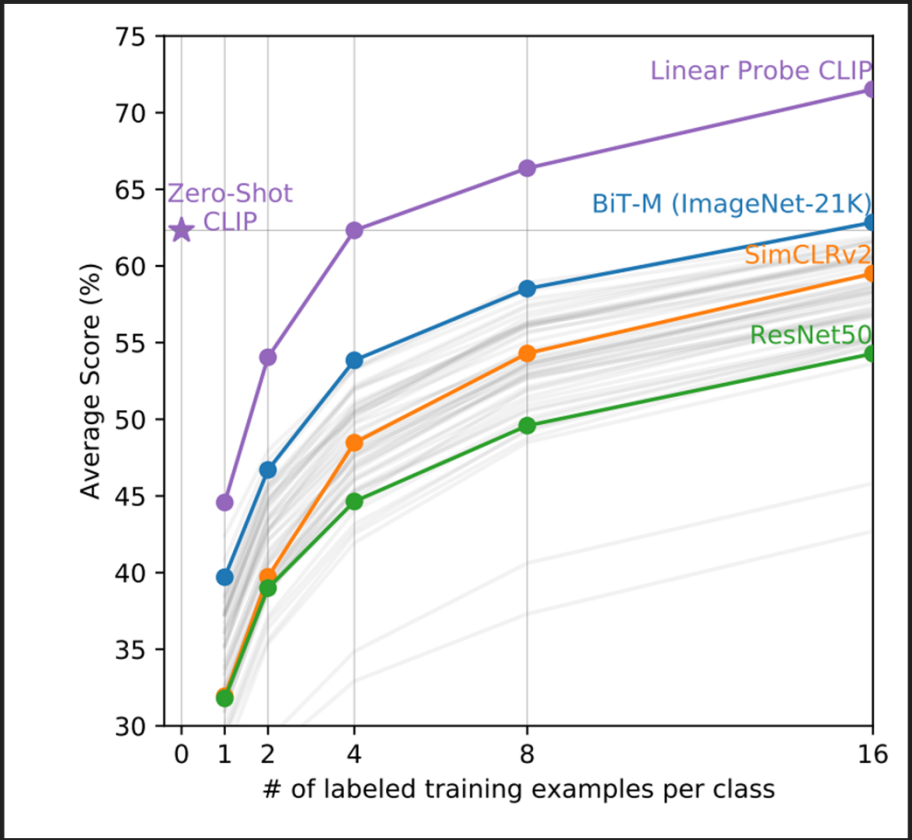


- Underperforms on many other datasets
- Mostly on specialized/complex datasets
- EuroSAT for satellite images, Tumor classification
- Makes intuitive sense, Zero-shot CLIP is highly generalized
- Not suited for hyper specific tasks unless fine-tuned

Zero-shot CLIP is much more robust

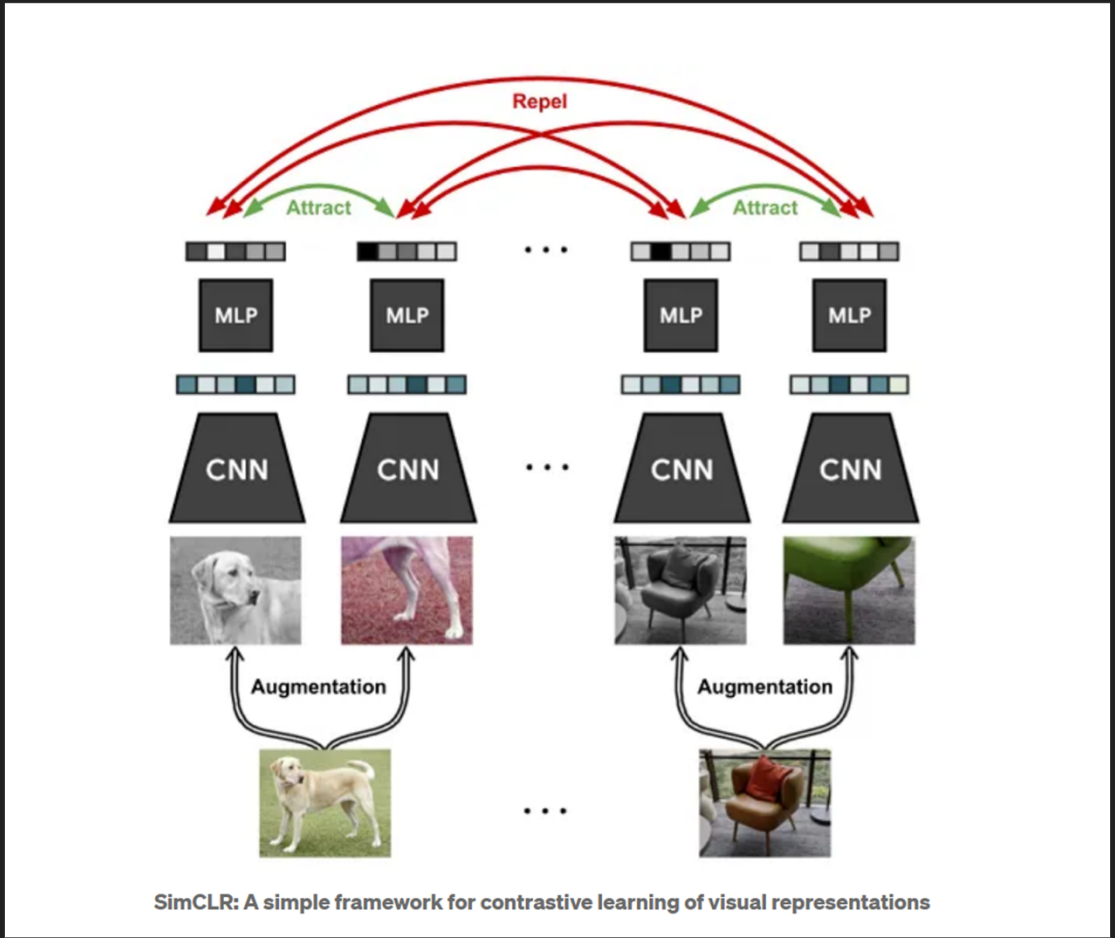


Results - Low-Shot



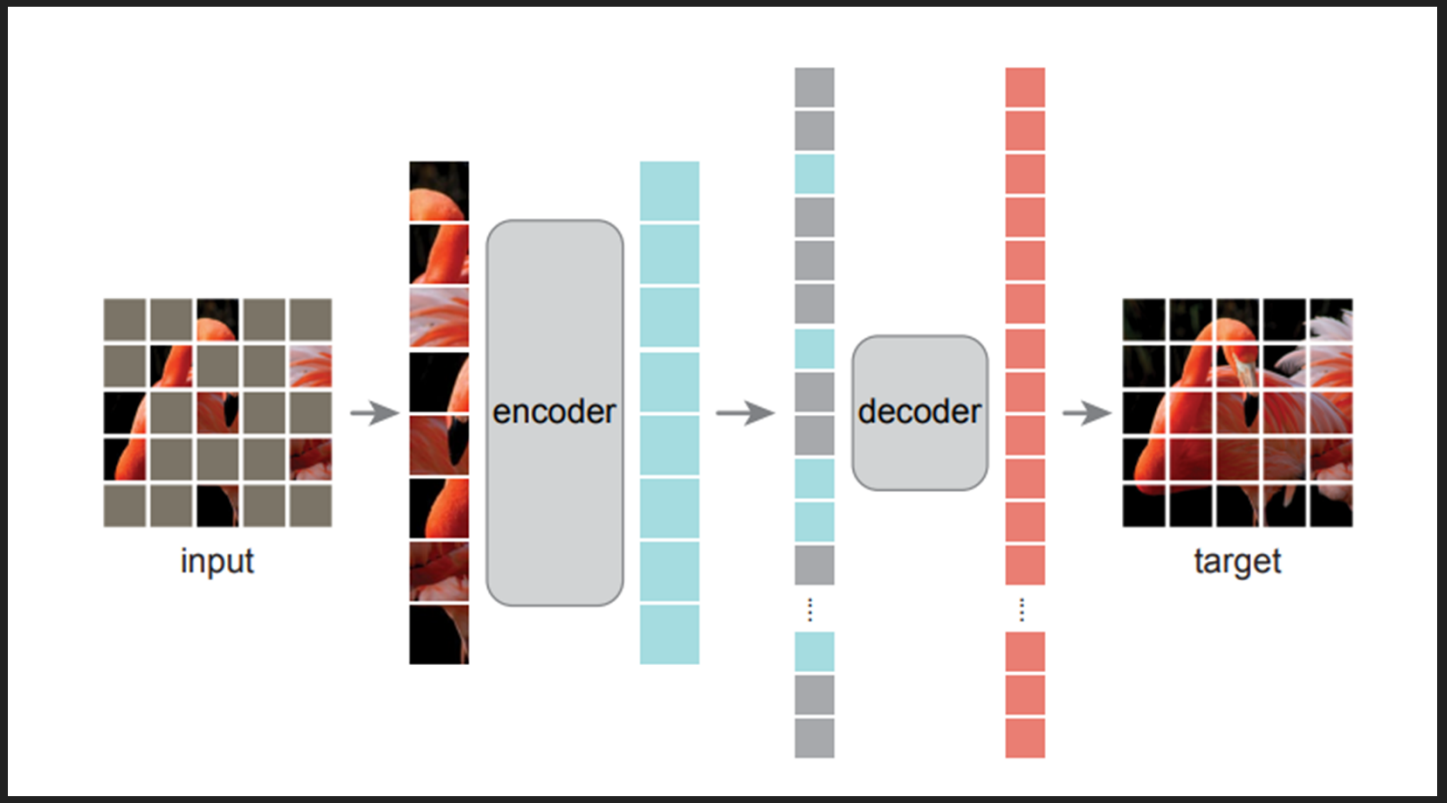
- CLIP scales well
- Linear-Probe CLIP climbs
- ResNet and other methods flatten
- Zero-Shot CLIP outperforms all non-CLIP methods up until 16 shot

Self-Supervised Learning: SimCLR

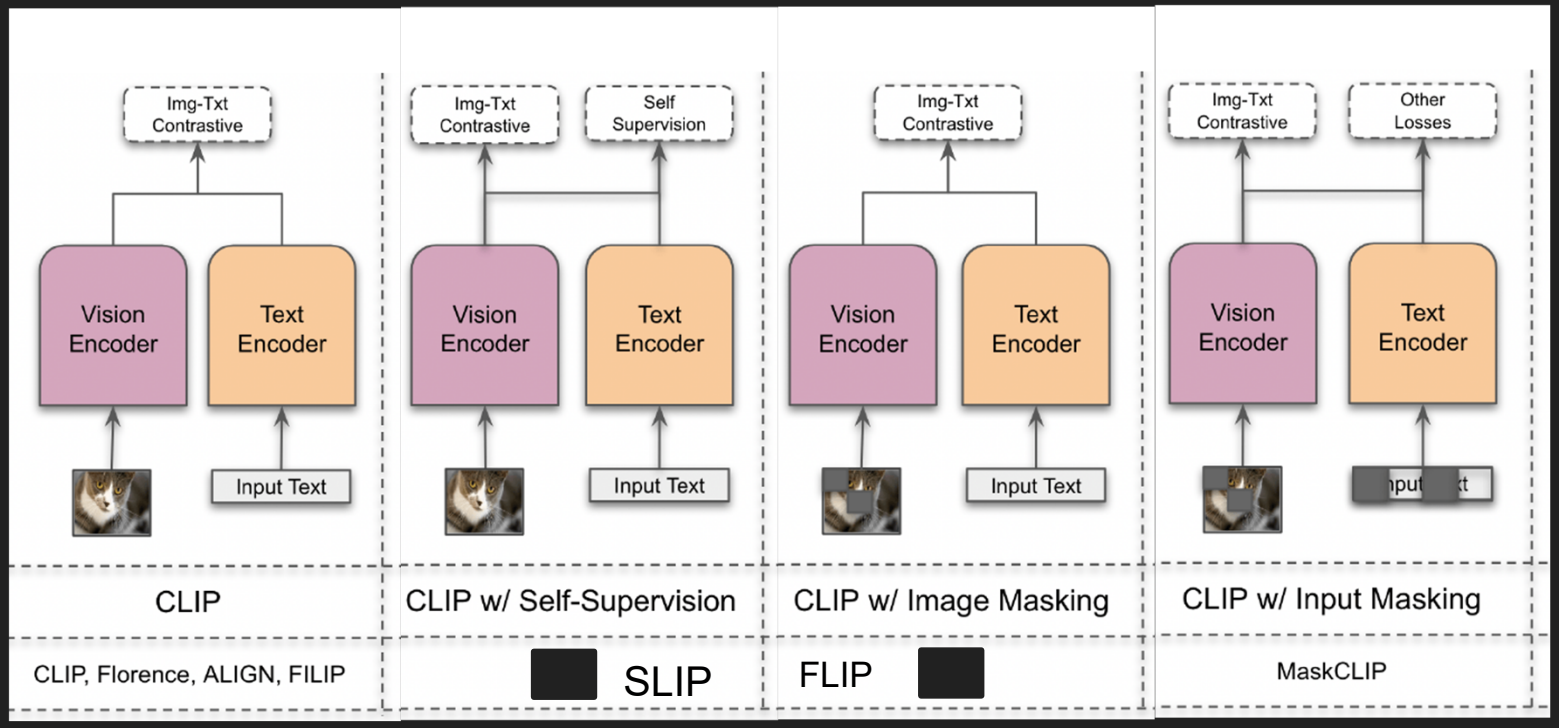


SimCLR: A simple framework for contrastive learning of visual representations

Self-Supervised Learning: MAE (Masked Auto-Encoder)



CLIP & Variants



Thank You