



Deep Learning 1

2025-2026 – Pascal Mettes

Lecture 9

Multi-modal deep learning

Previous lecture

Lecture	Title	Lecture	Title
1	Intro and history of deep learning	2	AutoDiff
3	Deep learning optimization I	4	Deep learning optimization II
5	Convolutional deep learning	6	Attention-based deep learning
7	Graph deep learning	8	From supervised to unsupervised deep learning
9	Multi-modal deep learning	10	Generative deep learning
11	What doesn't work in deep learning	12	Non-Euclidean deep learning
13	Q&A	14	Deep learning for videos

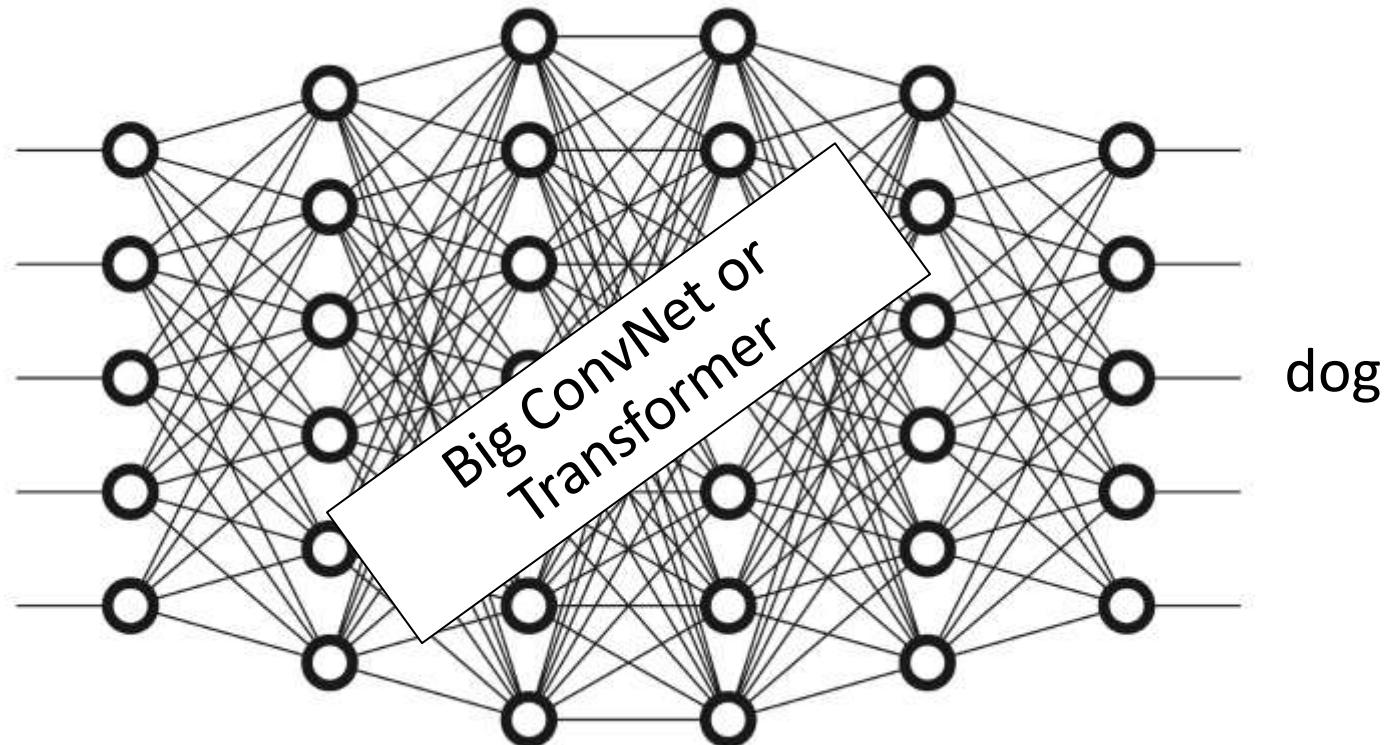
This lecture

Vision-language models.

Prompting and improving vision-language models.

Multi-modal LLMs.

Canonical supervised learning



Issues with supervised classification

Labels are deemed independent.

A false assumption. Any mistake is equally bad, which leads to real-world issues.

An image is more complex than a label.

An image is a complex scene, with multiple objects in interaction.

What happens when we see something we didn't train on?

We can never generalize to new settings.

Deep learning beyond class labels: the origins



Which bird species is this?

American Robin
White head
White belly

Crow
Black head
Black belly

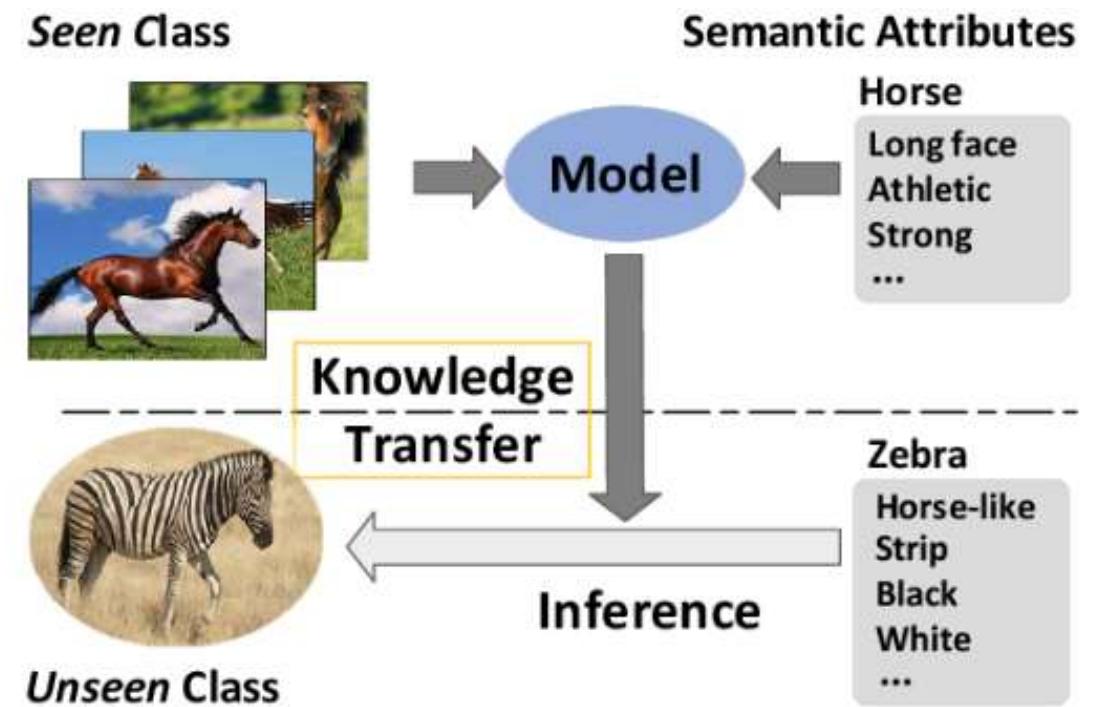
Painted Bunting (male)
Blue head
Red belly

Zero-shot learning

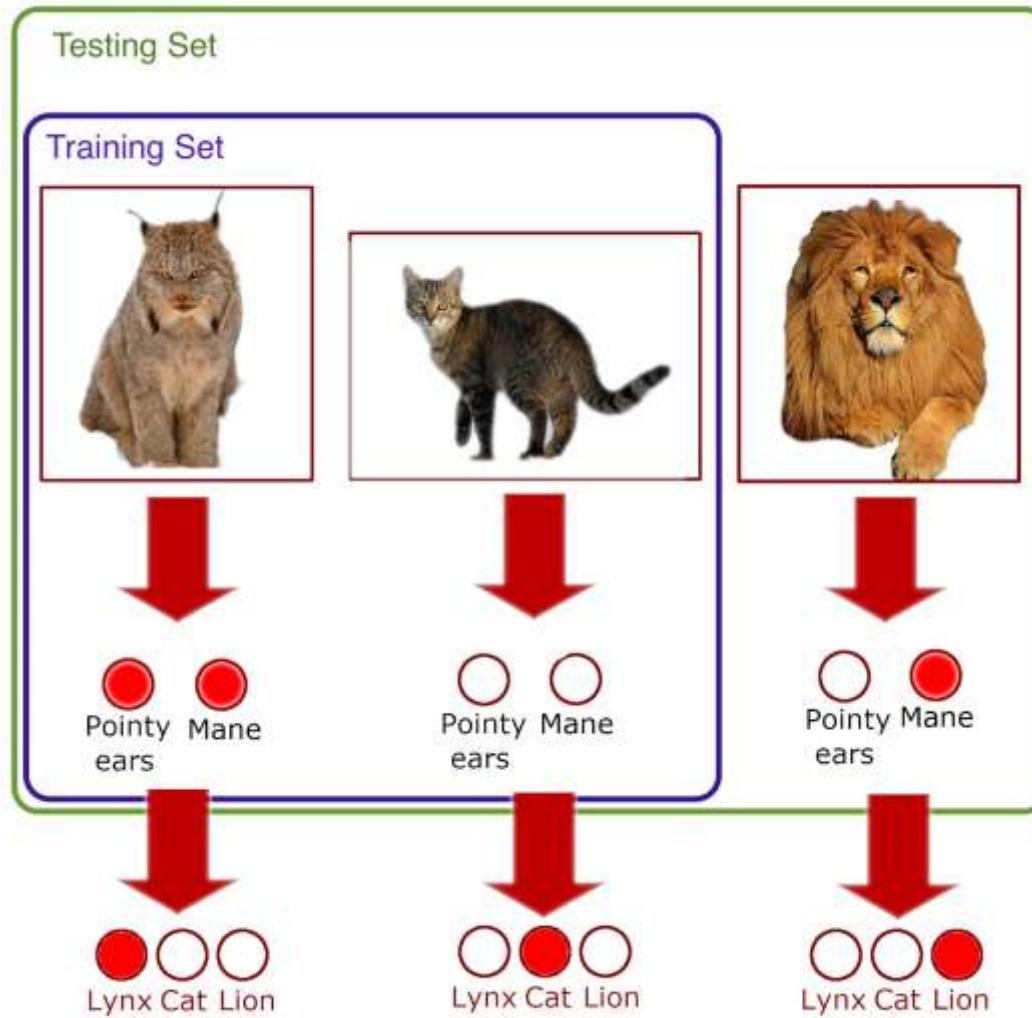
Original idea: Instead of predicting a class label per image, predict a set of shared attribute labels.

For each class, pre-specify the correct attributes.

During inference, predict all attributes and select class with highest attribute similarity.

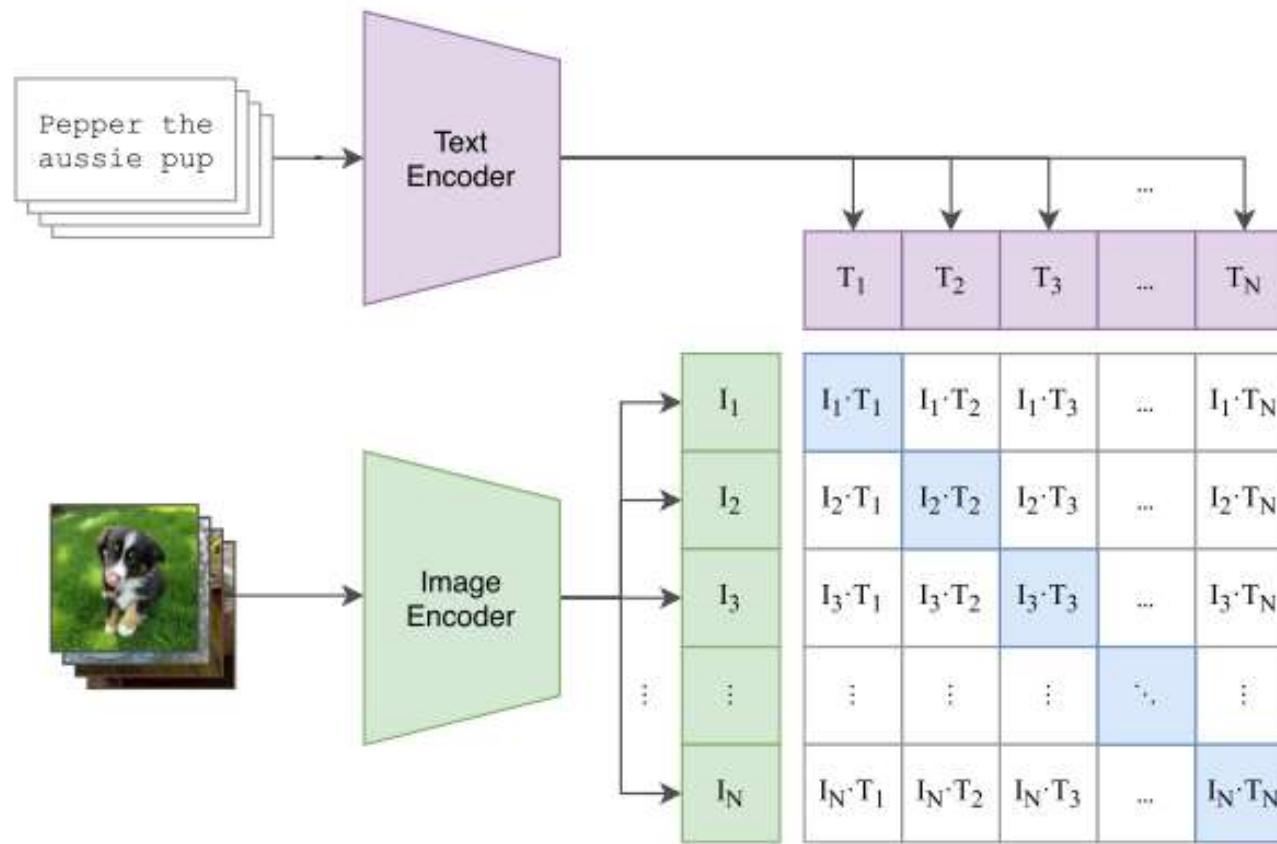


Recognition beyond the training set



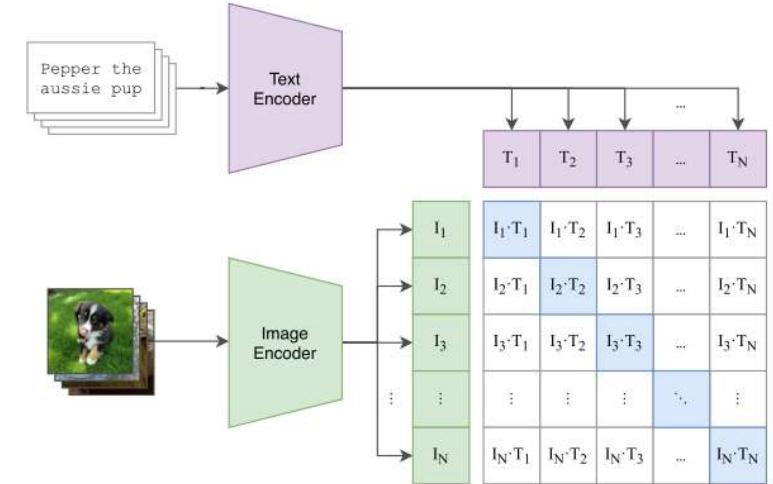
Vision-language models

CLIP: Contrastive Language-Image Pre-training



The idea behind CLIP

Treat semantics beyond labels.



Two encoders: one for an image, one for a sentence describing it.

Align both with a contrastive loss.

Pull image-text pair together, push other pairs in batch away.

Powerful approach, simple implementation

```
# 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]

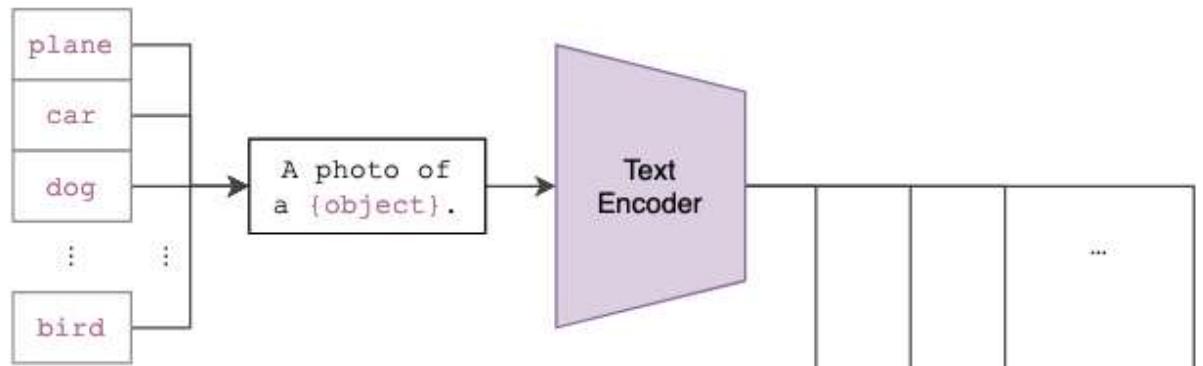
# joint multimodal embedding [n, d_e]
I_e = l2_normalize(np.dot(I_f, W_i), axis=1)
T_e = l2_normalize(np.dot(T_f, W_t), axis=1)

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

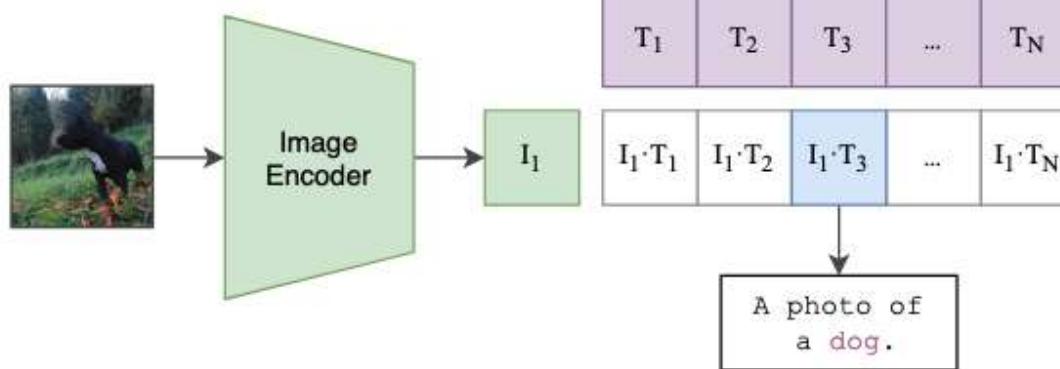
# symmetric loss function
labels = np.arange(n)
loss_i = cross_entropy_loss(logits, labels, axis=0)
loss_t = cross_entropy_loss(logits, labels, axis=1)
loss   = (loss_i + loss_t)/2
```

How to use CLIP for “normal” classification?

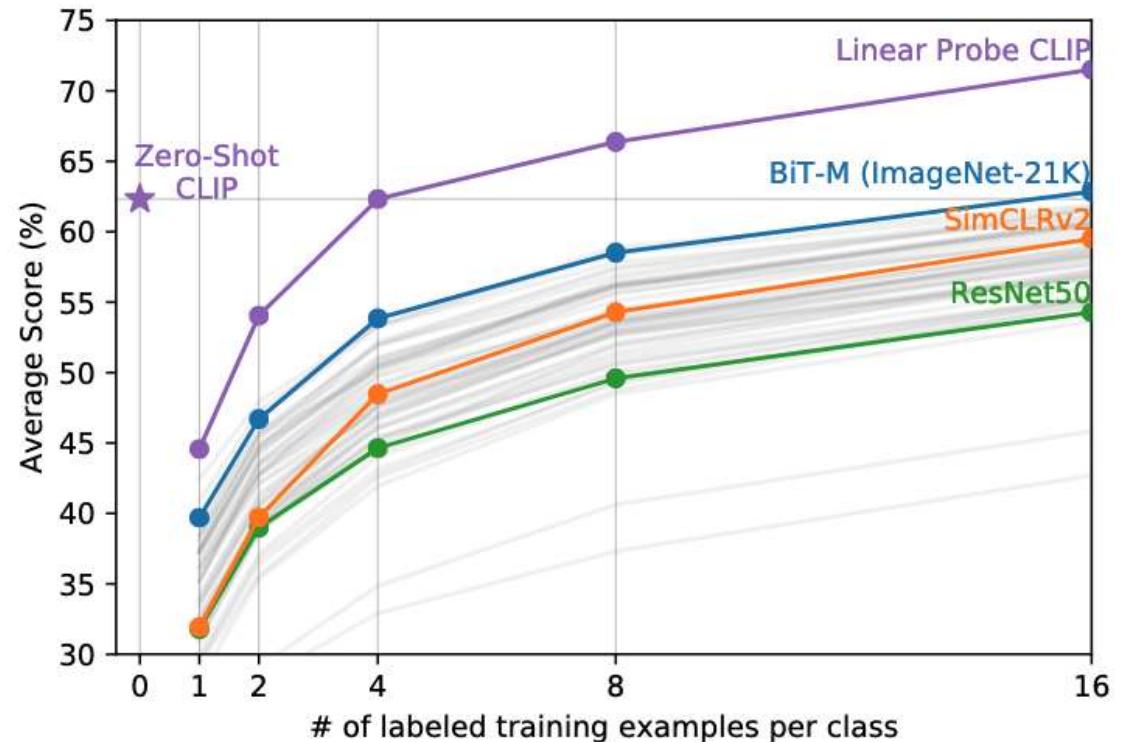
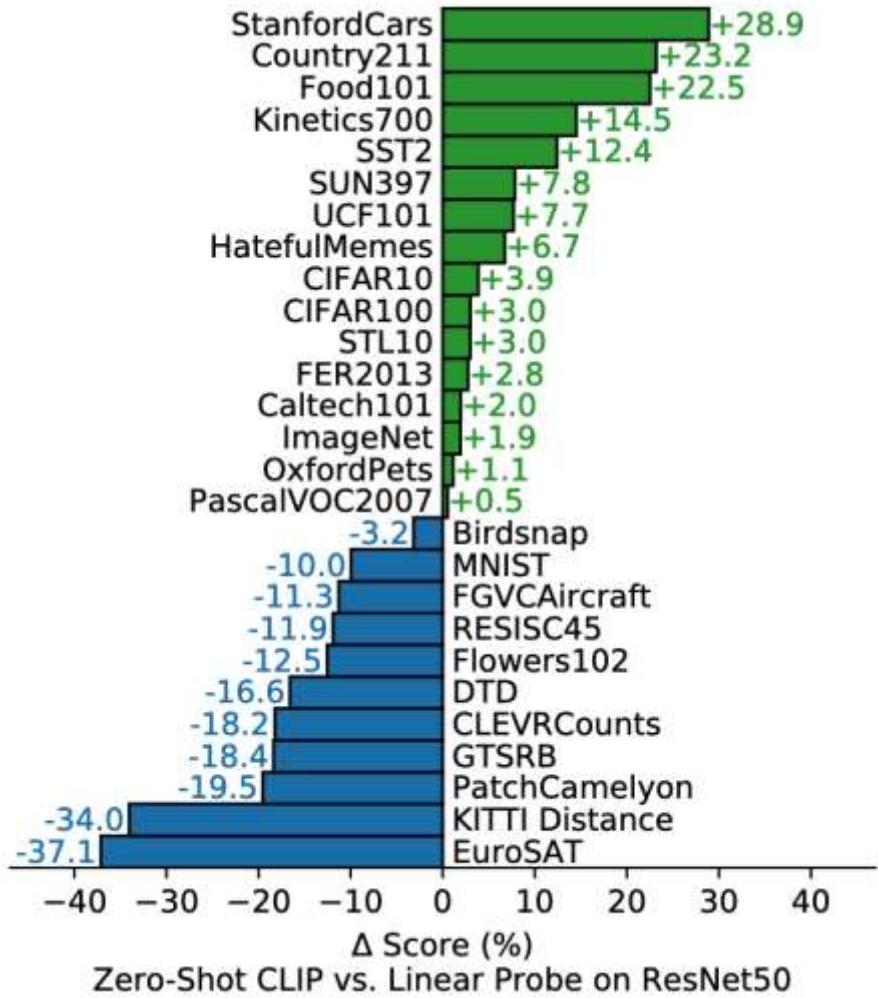
(2) Create dataset classifier from label text



(3) Use for zero-shot prediction



Pre-training is so powerful, no training needed



Keys behind the success of CLIP

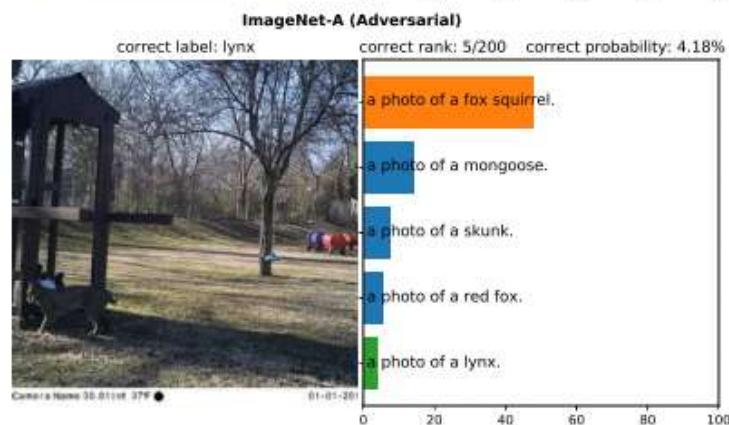
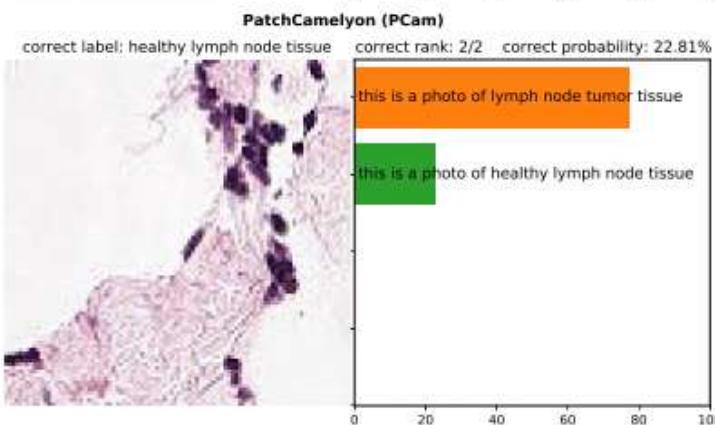
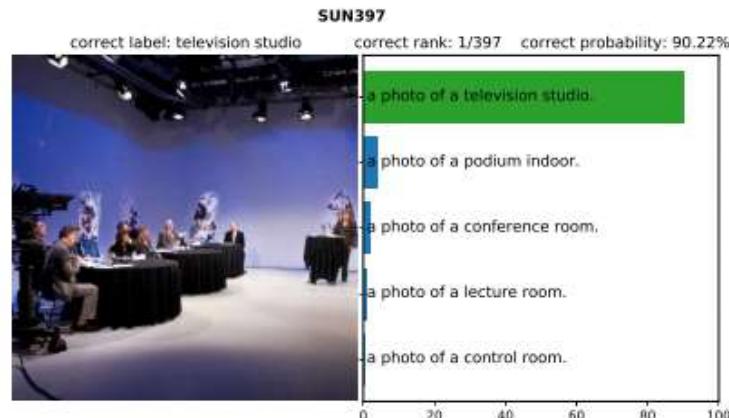
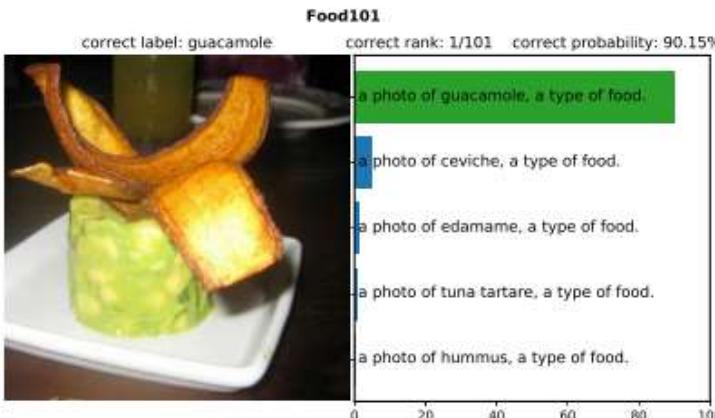
Pre-training on up to 5 billion image-text pairs (~100x bigger than ImageNet).

Sentences are more complex than labels.

Semantics is treated as continuous instead of discrete.

Zero-shot examples of CLIP

Predicted probability of top 5 classes for each example.



Robustness of CLIP

	Dataset Examples		ImageNet	Zero-Shot	Δ Score
	ResNet101	CLIP			
ImageNet			76.2	76.2	0%
ImageNetV2			64.3	70.1	+5.8%
ImageNet-R			37.7	88.9	+51.2%
ObjectNet			32.6	72.3	+39.7%
ImageNet Sketch			25.2	60.2	+35.0%
ImageNet-A			2.7	77.1	+74.4%

Visualizing distribution shift for bananas, a class shared across 5 of the 7 natural distribution shift datasets.

		Food101	CIFAR10	CIFAR100	Bindnup	SUN397	Cars	Aircraft	VOC2007	DTD	Pets	Caltech101	Flowers	MNIST	FER2013	STL10*	EuroSAT	RESC45	GTSRB	KITTI	Country211	PCAM	UCF101	Kinetics700	CLEVR	HasItMeme	SST	ImageNet
LM RN50		81.3	82.8	61.7	44.2	69.6	74.9	44.9	85.5	71.5	82.8	85.5	91.1	96.6	60.1	95.3	93.4	84.0	73.8	70.2	19.0	82.9	76.4	51.9	51.2	65.2	76.8	65.2
CLIP-RN	50	86.4	88.7	70.3	56.4	73.3	78.3	49.1	87.1	76.4	88.2	89.6	96.1	98.3	64.2	96.6	95.2	87.5	82.4	70.2	25.3	82.7	81.6	57.2	53.6	65.7	72.6	73.3
	101	88.9	91.1	73.5	58.6	75.1	84.0	50.7	88.0	76.3	91.0	92.0	96.4	98.4	65.2	97.8	95.9	89.3	82.4	73.6	26.6	82.8	84.0	60.3	50.3	68.2	73.3	75.7
	50x4	91.3	90.5	73.0	65.7	77.0	85.9	57.3	88.4	79.5	91.9	92.5	97.8	98.5	68.1	97.8	96.4	89.7	85.5	59.4	30.3	83.0	85.7	62.6	52.5	68.0	76.6	78.2
	50x16	93.3	92.2	74.9	72.8	79.2	88.7	62.7	89.0	79.1	93.5	93.7	98.3	98.9	68.7	98.6	97.0	91.4	89.0	69.2	34.8	83.5	88.0	66.3	53.8	71.1	80.0	81.5
	50x64	94.8	94.1	78.6	77.2	81.1	90.5	67.7	88.9	82.0	94.5	95.4	98.9	98.9	71.3	99.1	97.1	92.8	90.2	69.2	40.7	83.7	89.5	69.1	55.0	75.0	81.2	83.6
CLIP-ViT	B/32	88.8	95.1	80.5	58.5	76.6	81.8	52.0	87.7	76.5	90.0	93.0	96.9	99.0	69.2	98.3	97.0	90.5	85.3	66.2	27.8	83.9	85.5	61.7	52.1	66.7	70.8	76.1
	B/16	92.8	96.2	83.1	67.8	78.4	86.7	59.5	89.2	79.2	93.1	94.7	98.1	99.0	69.5	99.0	97.1	92.7	86.6	67.8	33.3	83.5	88.4	66.1	57.1	70.3	75.5	80.2
	L/14	95.2	98.0	87.5	77.0	81.8	90.9	69.4	89.6	82.1	95.1	96.5	99.2	99.2	72.2	99.7	98.2	94.1	92.5	64.7	42.9	85.8	91.5	72.0	57.8	76.2	80.8	83.9
	L/14-336px	95.9	97.9	87.4	79.9	82.2	91.5	71.6	89.9	83.0	95.1	96.0	99.2	99.2	72.9	99.7	98.1	94.9	92.4	69.2	46.4	85.6	92.0	73.0	60.3	77.3	80.5	85.4

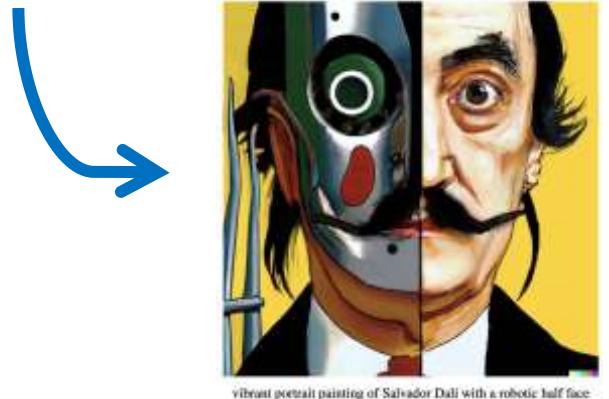
Performance of various pre-trained models over 27 datasets

Using CLIP in other models

The joint multimodal embedding space of CLIP enables its usage in many other downstream tasks in a zero-shot fashion.

- DALLE-2¹ – a text-guided image generation model,
- CLIP4Clip² - video-language retrieval model,
- GroupViT³ – semantic segmentation model - in a zero-shot manner.

“Vibrant portrait painting of Salvador Dalí with a robotic half.”

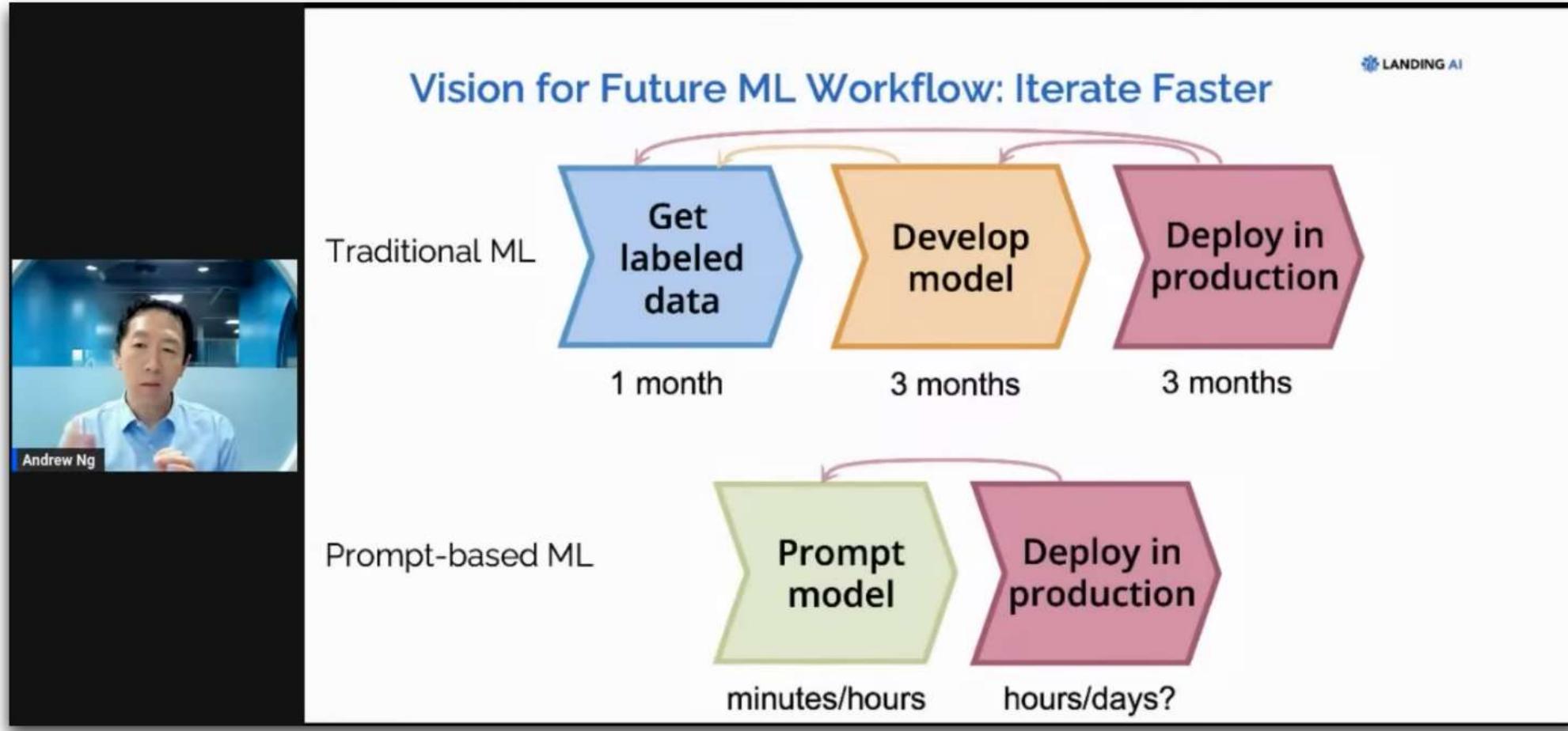


¹ Hierarchical Text-Conditional Image Generation with CLIP Latents, Ramesh et al. (2022)

² CLIP4Clip: An Empirical Study of CLIP for End to End Video Clip Retrieval , Luo et al. (2022)

³ GroupViT: Semantic Segmentation Emerges from Text Supervision, Xu et al. (2022)

A peek into the future



Limitations of CLIP

Models like CLIP simply provide a similarity score between text and image.

Lack the ability to generate language - less suitable to more open-ended tasks.

Require a fixed prompt mechanism to deal with standard classification.

Uses short context windows, ignore hierarchies.

Fine-tuning can actually decrease performance.

Prompt engineering

a bad photo of a {}.
a photo of many {}.
a sculpture of a {}.
a photo of the hard to see {}.
a low resolution photo of the {}.
a rendering of a {}.
graffiti of a {}.
a bad photo of the {}.
a cropped photo of the {}.
a tattoo of a {}.
the embroidered {}.
a photo of a hard to see {}.
a bright photo of a {}.
a photo of a clean {}.
a photo of a dirty {}.
a dark photo of the {}.
a drawing of a {}.
a photo of my {}.
the plastic {}.
a photo of the cool {}.
a close-up photo of a {}.
a black and white photo of the {}.
a painting of the {}.
a painting of a {}.

a pixelated photo of the {}.
a sculpture of the {}.
a bright photo of the {}.
a cropped photo of a {}.
a plastic {}.
a photo of the dirty {}.
a jpeg corrupted photo of a {}.
a blurry photo of the {}.
a photo of the {}.
a good photo of the {}.
a rendering of the {}.
a {} in a video game.
a photo of one {}.
a doodle of a {}.
a close-up photo of the {}.
a photo of a {}.
the origami {}.
the {} in a video game.
a sketch of a {}.
a doodle of the {}.
a origami {}.
a low resolution photo of a {}.
the toy {}.
a rendition of the {}.

a photo of the clean {}.
a photo of a large {}.
a rendition of a {}.
a photo of a nice {}.
a photo of a weird {}.
a blurry photo of a {}.
a cartoon {}.
art of a {}.
a sketch of the {}.
a embroidered {}.
a pixelated photo of a {}.
itap of the {}.
a jpeg corrupted photo of the {}.
a good photo of a {}.
a plushie {}.
a photo of the nice {}.
a photo of the small {}.
a photo of the weird {}.
the cartoon {}.
art of the {}.
a drawing of the {}.
a photo of the large {}.
a black and white photo of a {}.
the plushie {}.

A slight change in wording could lead to big changes in performance

https://github.com/openai/CLIP/blob/main/notebooks/Prompt_Engineering_for_ImageNet.ipynb

The effect of prompt engineering

Dataset	Prompt	Accuracy
Caltech101	a [CLASS].	82.68
	a photo of [CLASS].	80.81
	a photo of a [CLASS].	86.29
	[V] ₁ [V] ₂ ... [V] _M [CLASS].	91.83
Flowers102	a photo of a [CLASS].	60.86
	a flower photo of a [CLASS].	65.81
	a photo of a [CLASS], a type of flower .	66.14
	[V] ₁ [V] ₂ ... [V] _M [CLASS].	94.51
Describable Textures (DTD)	a photo of a [CLASS].	39.83
	a photo of a [CLASS] texture .	40.25
	[CLASS] texture.	42.32
	[V] ₁ [V] ₂ ... [V] _M [CLASS].	63.58
EuroSAT	a photo of a [CLASS].	24.17
	a satellite photo of [CLASS].	37.46
	a centered satellite photo of [CLASS].	37.56
	[V] ₁ [V] ₂ ... [V] _M [CLASS].	83.53

A slight change in wording could lead to big changes in performance

What makes a good prompt?

A person riding a
motorcycle on a dirt road.



Two dogs play in the grass.



Can we learn to prompt instead?

Caltech101



Prompt	Accuracy
a [CLASS].	82.68
a photo of [CLASS].	80.81
a photo of a [CLASS].	86.29
[V] ₁ [V] ₂ ... [V] _M [CLASS].	91.83

(a)

Flowers102



Prompt	Accuracy
a photo of a [CLASS].	60.86
a flower photo of a [CLASS].	65.81
a photo of a [CLASS], a type of flower.	66.14
[V] ₁ [V] ₂ ... [V] _M [CLASS].	94.51

(b)

Describable Textures (DTD)



Prompt	Accuracy
a photo of a [CLASS].	39.83
a photo of a [CLASS] texture.	40.25
[CLASS] texture.	42.32
[V] ₁ [V] ₂ ... [V] _M [CLASS].	63.58

(c)

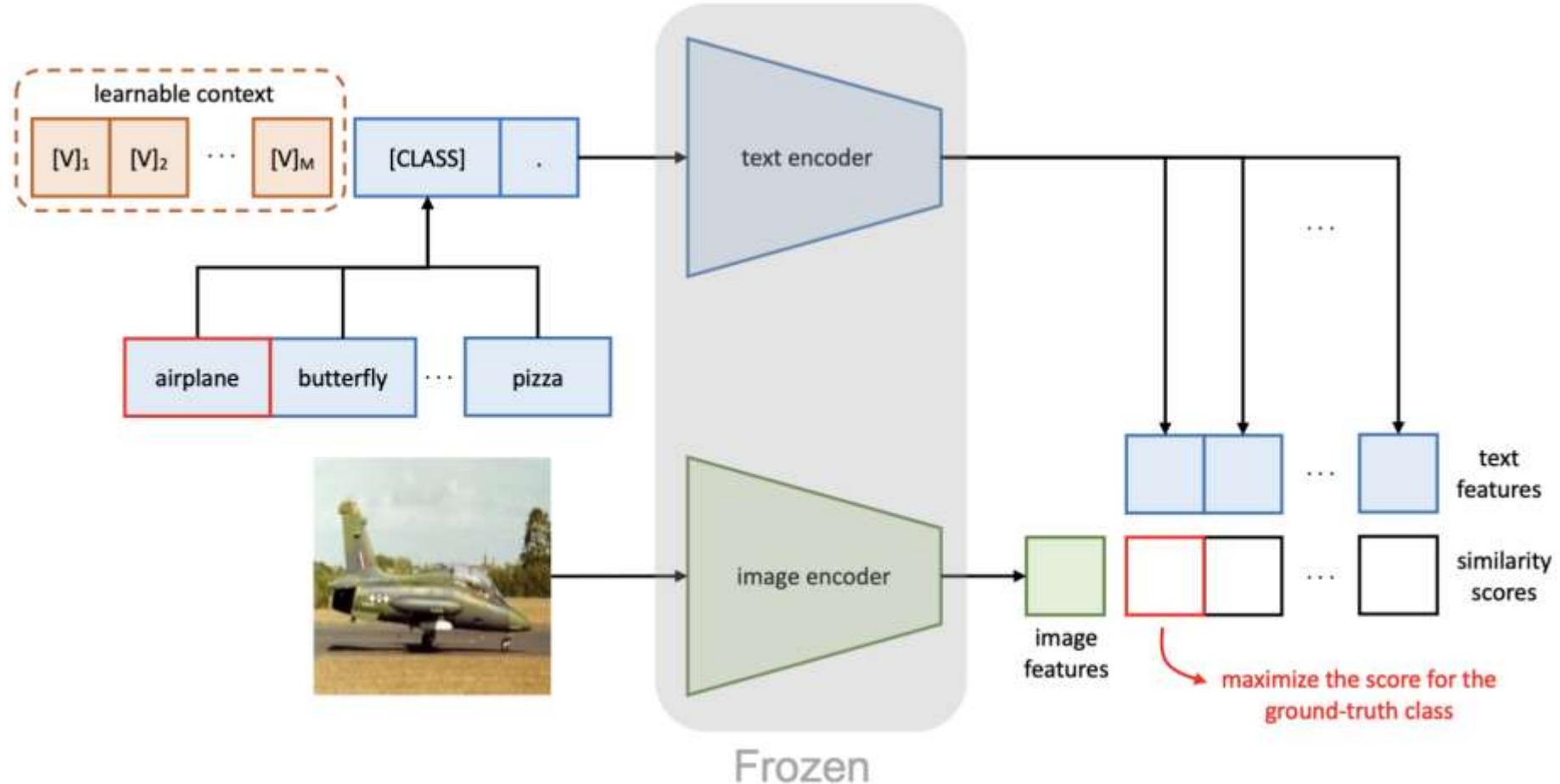
EuroSAT



Prompt	Accuracy
a photo of a [CLASS].	24.17
a satellite photo of [CLASS].	37.46
a centered satellite photo of [CLASS].	37.56
[V] ₁ [V] ₂ ... [V] _M [CLASS].	83.53

(d)

Learning to prompt for vision-language models

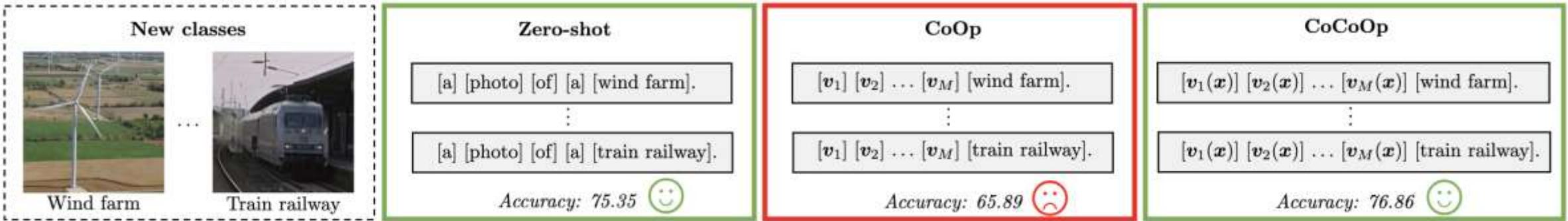


CoCoOp: Beyond statically learned prompts

Issue in CoOp: The prompt is overfit to wider unseen classes.

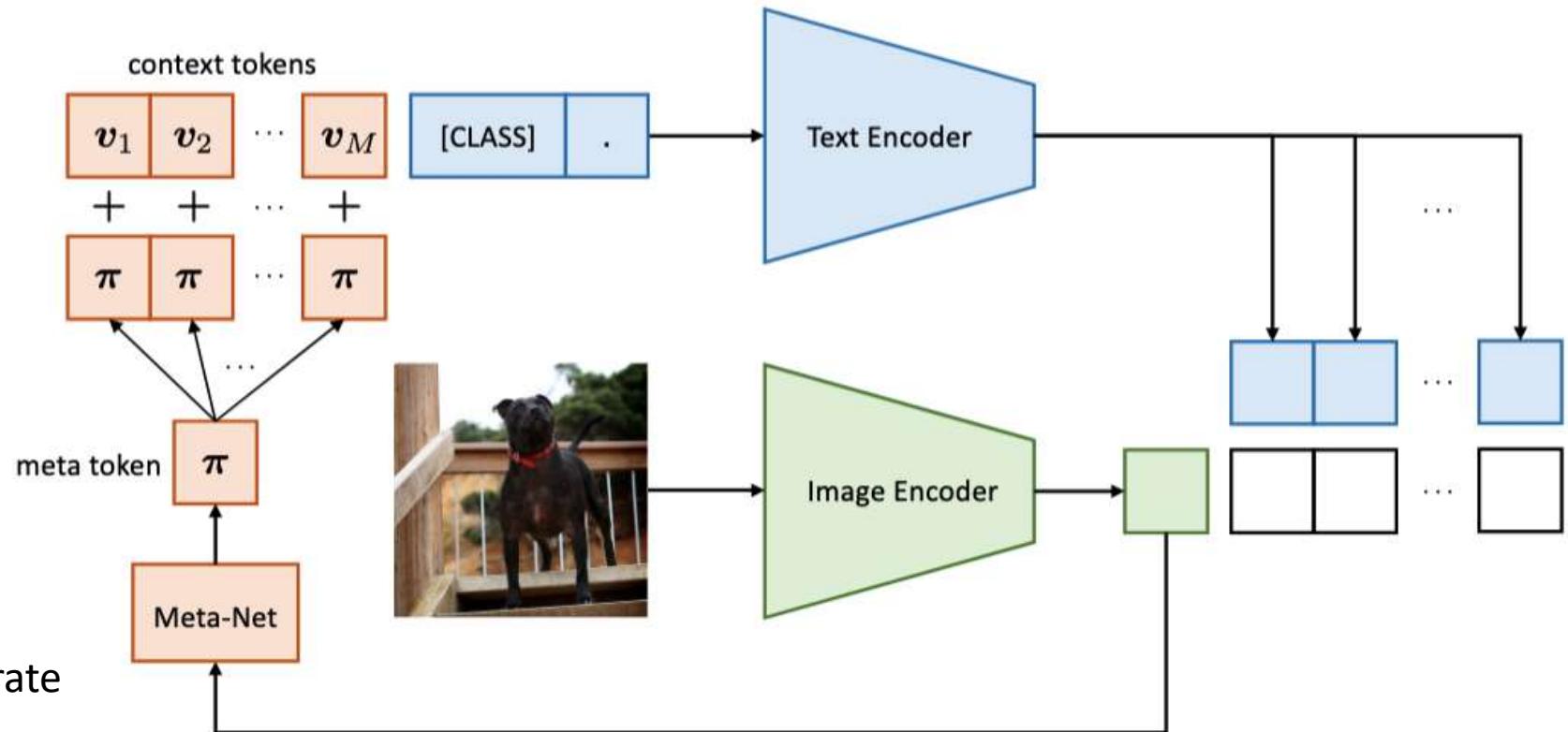
Why?

The prompt embeddings ignore the visual instance.



Conditional prompt learning

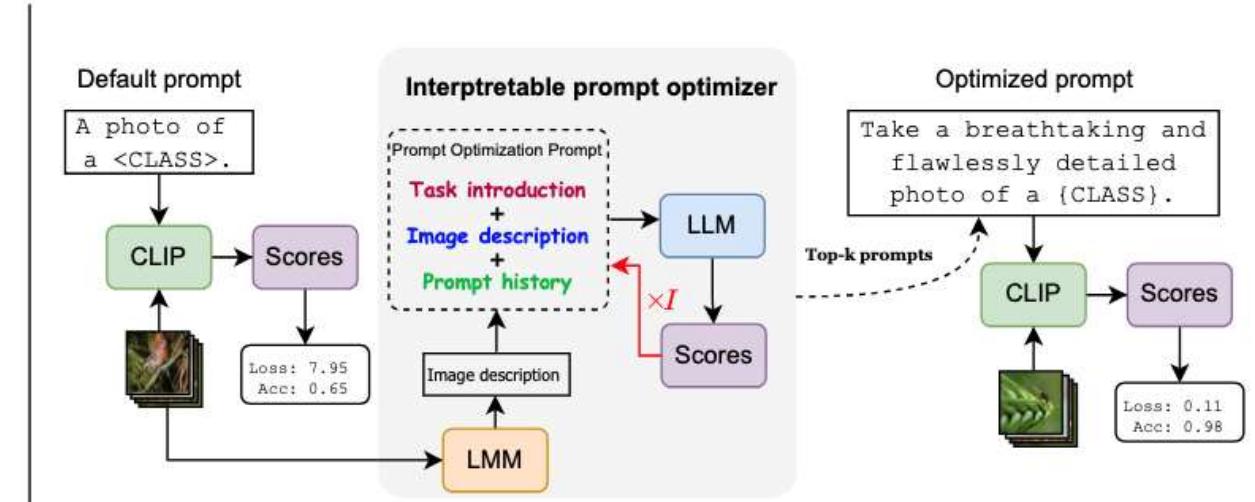
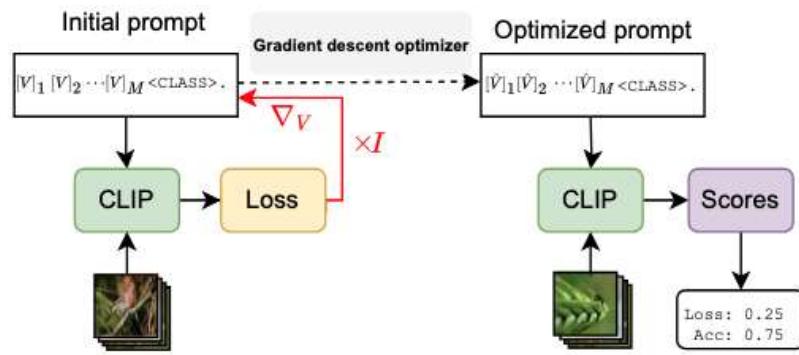
Component 1:
Context vectors (ala CoOp).



Component 2:
Small network that learns to generate
an image-conditional token.

Interpretable prompt learning

Issue with all prompt learners: we have no clue what they learned.



(a) Gradient-based prompt optimization.

(b) Interpretable prompt optimization.

Summarizing prompts

Prompts make it possible to have in-context generalization.

First attempt: manually curate a prompt.

Prompt learning optimizes prompt tokens, massively improving results.

Interpretable prompt learning makes prompt learning understandable, but require LLM probes (which can become quite expensive).

Break

Looking beyond CLIP

In CLIP, the text encoder is learnt from scratch, why not start from an LLM?

How to efficiently fine-tune VLMs?

What about other modalities?

CLIP is flat, but the real-world is hierarchical. How can we fix this?

Using an LLM: Flamingo

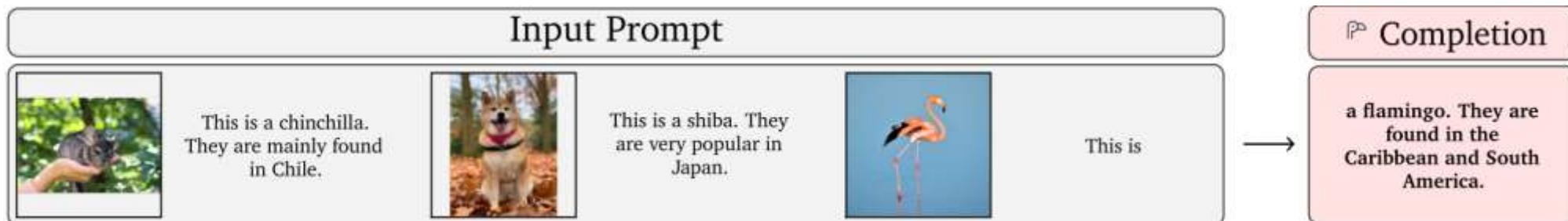
Flamingo is a Transformer-based architecture for multimodal few-shot tasks (image captioning, visual dialogue or visual question answering).

Able to learn from only a few input/output examples i.e., *in few-shot settings*.

It processes arbitrarily interleaved images and text as prompt;

And it generates output text in an open-ended manner.

Performs in-context learning (like GPT) but with images and text as context.



Pre-training Flamingo

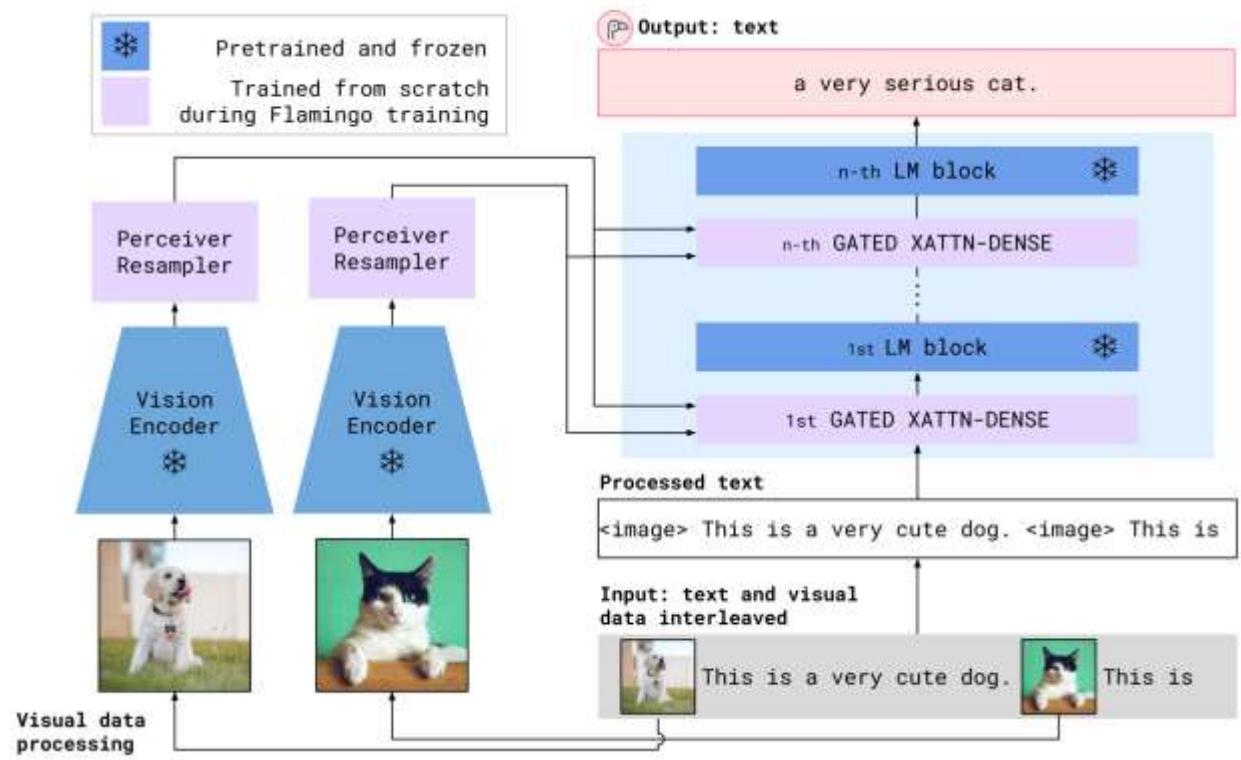
Vision side: an encoder with contrastive text-image approach, à la CLIP.

Language side: existing autoregressive LM trained on a large text corpus.

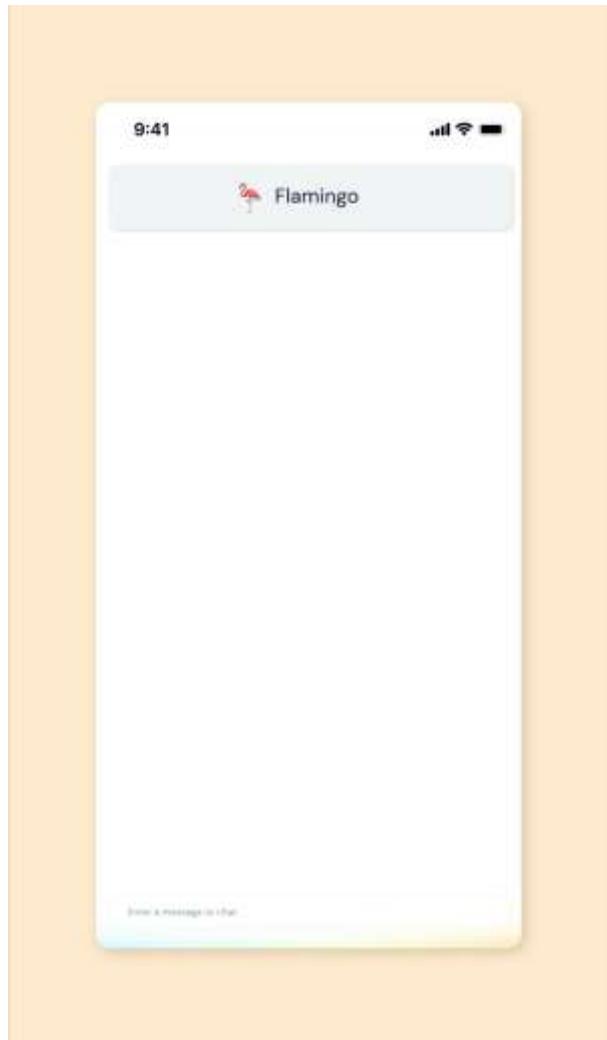
Linked via a learnable attention component (the Perceiver).

It outputs a fixed-size set of visual tokens.

Which are used to condition the frozen LM, trained to generate text.



Example output of Flamingo



Which city is this?



This is a street sign in New York City.



Which street corner is it?



It is the intersection of Madison Avenue and East 42nd Street.



Which subway station is nearby?



The closest subway station is Grand Central Station.

I would like you to read the color and then say the color it is written in. For example:

PURPLE



Color is "Purple" and it is written in red.

GREEN



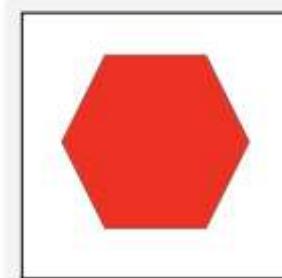
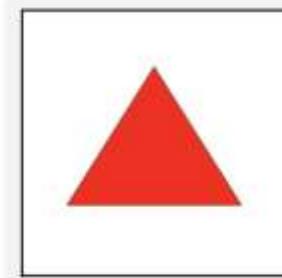
Color is "Green" and it is written in blue.

YELLOW



Color is "Yellow" and it is written in green.

BLACK



What is the difference between these two images?

The first one is a triangle and the second one is a hexagon.



Which one has larger internal angles?

The hexagon has larger internal angles.



Looking beyond CLIP

In CLIP, the text encoder is learnt from scratch, why not start from an LLM?

How to efficiently fine-tune VLMs?

What about other modalities?

CLIP is flat, but the real-world is hierarchical. How can we fix this?

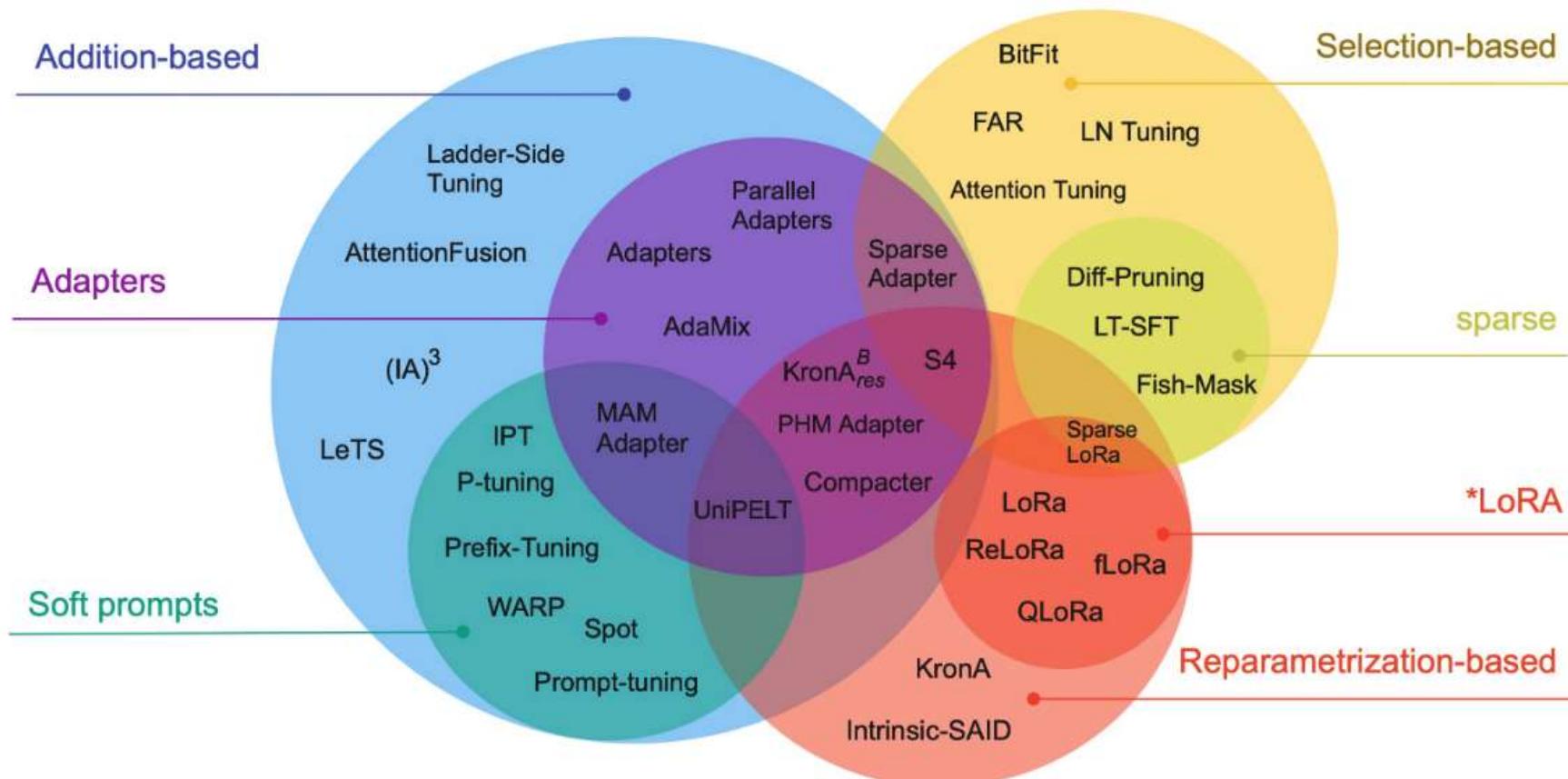
Fine-tuning VLMs

Sometimes, in-context learning is not enough, we need to alter the parameters.

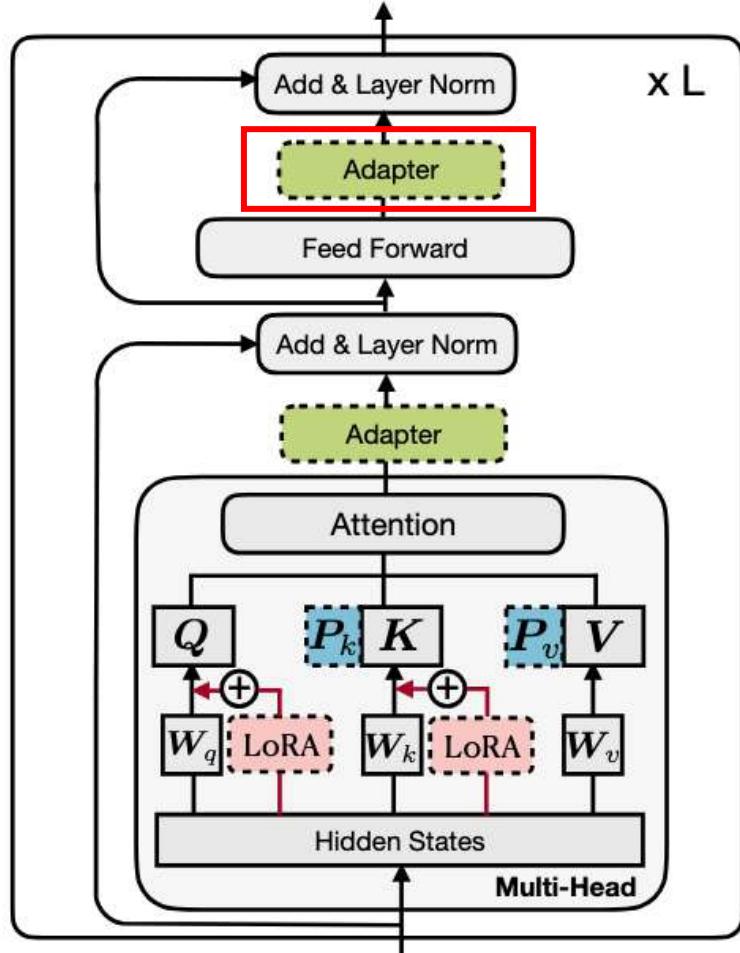
E.g., when exposed to a new task, new language, or any other new scope.

Problem! LLMs have huge networks. Us poor common folk cannot simply update a 10B parameter network.

Parameter efficient fine-tuning



Adding adapters

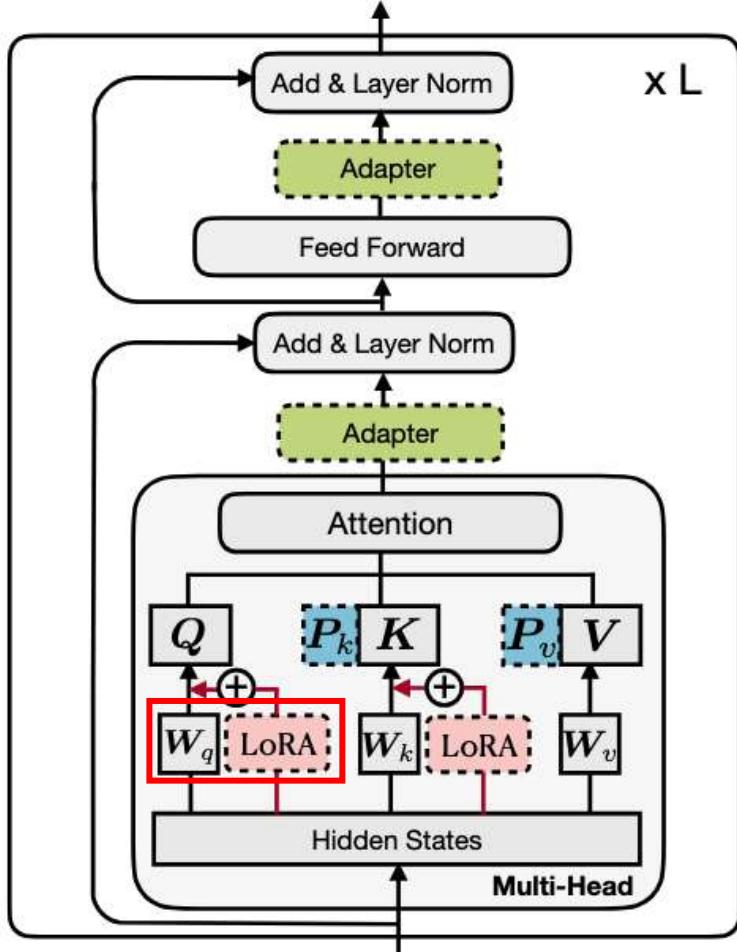


Let's add some small network blocks.

During fine-tuning, we keep the main architecture fixed and only tune the adapters.

Strong performance while only needing a full computation graph of a small subset.

Adding LoRA

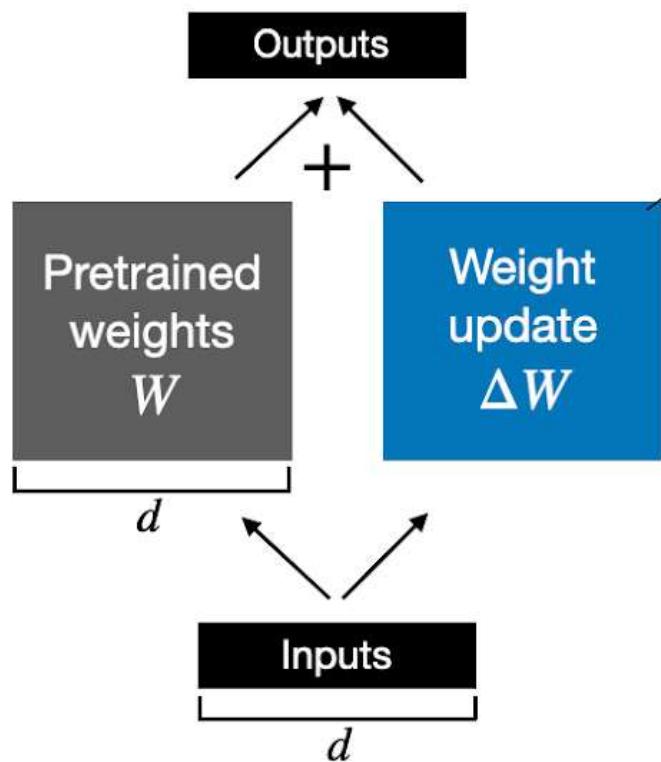


Most of the parameters of transformers are in the linear layers. Maybe these such matrices has a lower intrinsic dimensionality?

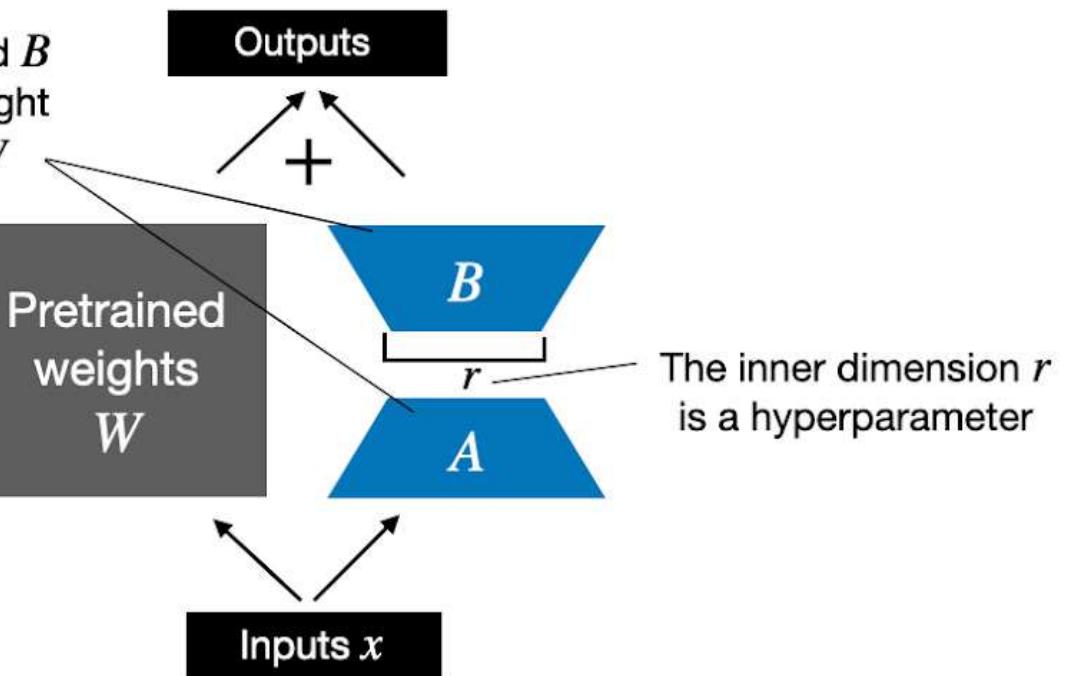
Can we learn a low-rank approximation of these huge matrices during fine-tuning?

LoRA

Weight update in regular finetuning



LoRA matrices A and B approximate the weight update matrix ΔW



The inner dimension r is a hyperparameter

Looking beyond CLIP

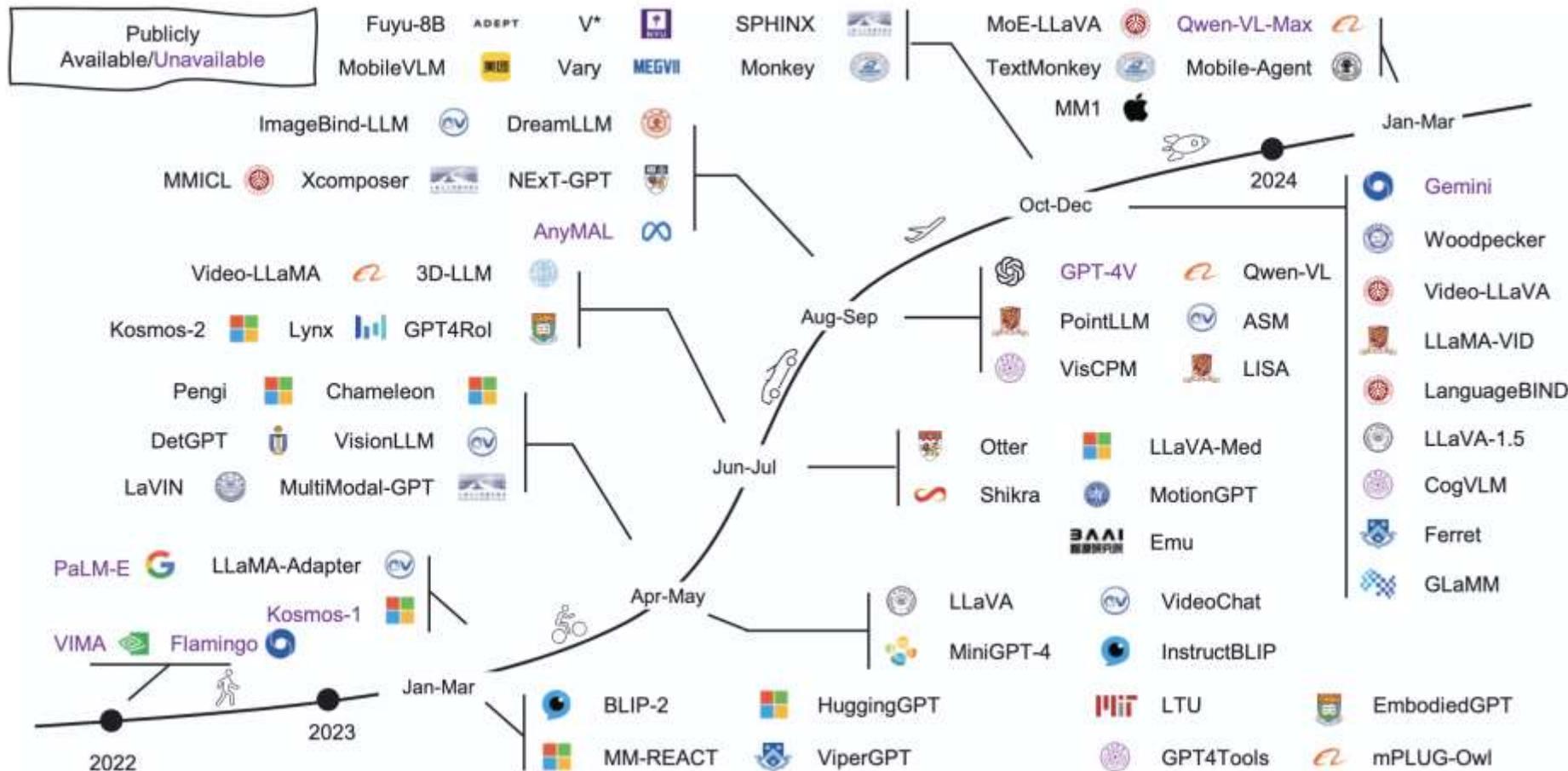
In CLIP, the text encoder is learnt from scratch, why not start from an LLM?

How to efficiently fine-tune VLMs?

What about other modalities?

CLIP is flat, but the real-world is hierarchical. How can we fix this?

Multimodal Large Language Models



"A survey on multimodal large language models." Yin et al. NSR 2024.

Main idea of MLLMs

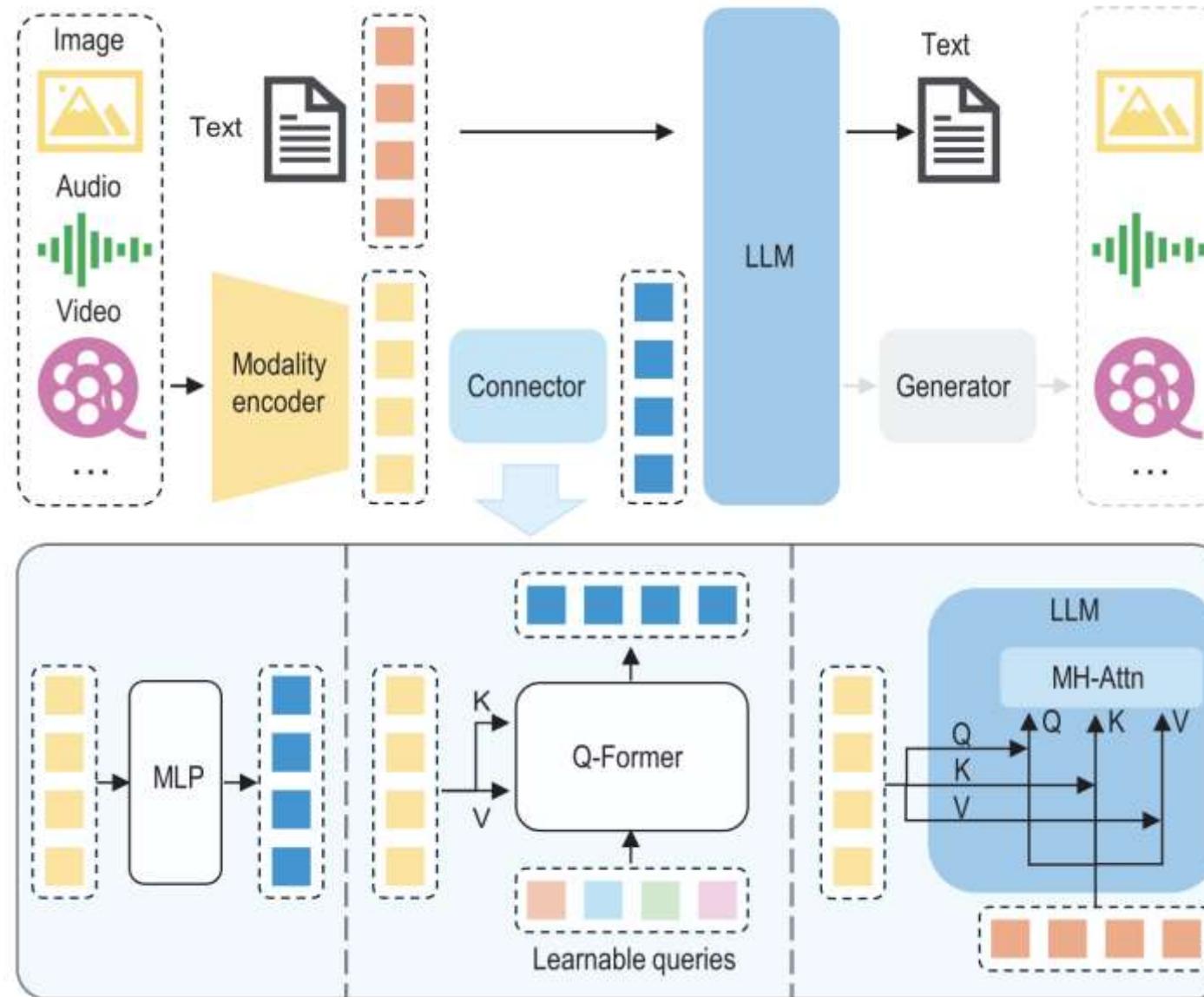
More is more: different modalities provide complimentary views.

For example, visually a bike is close to a motor and far from a leafblower.

In audio however, the motor and leafblower are close, far from a bike.

You can soon expect extensions of popular LLMs to video, audio, and more.

Multimodal Large Language Model framework



Case study 1: MLLMs and video popularity

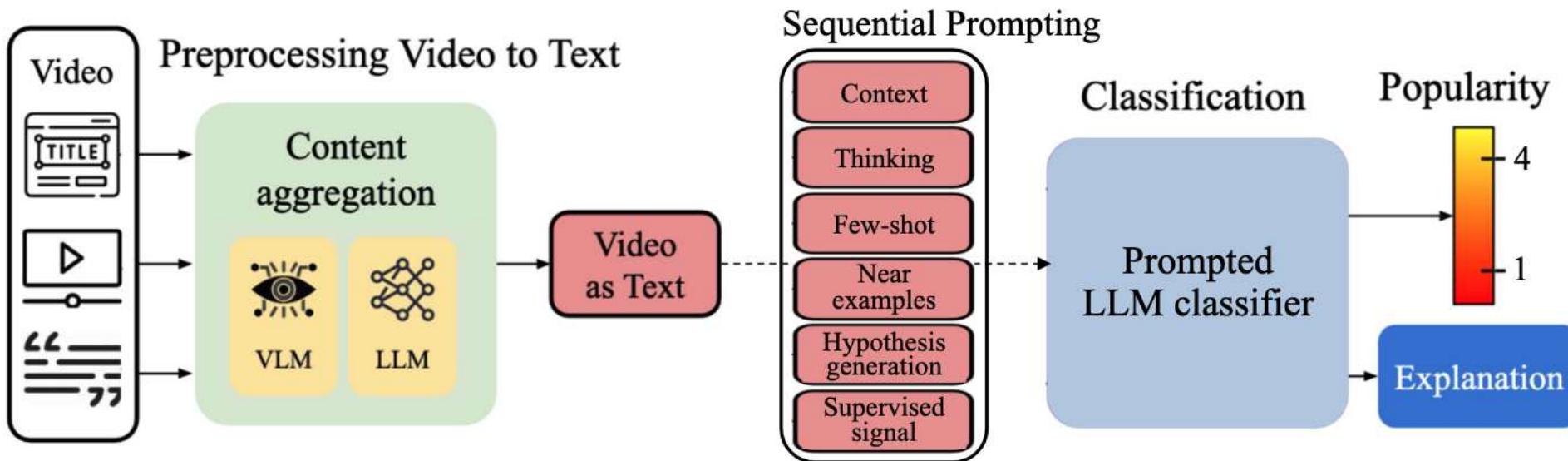
Video-based MLLMs can deal with concrete tasks, such as object recognition.

Video popularity is however cultural, social, and time-dependent.

Is it possible for an MLLM to predict whether a video will be popular, without fine-tuning the modal to this task?

Case study 1: MLLMs and video popularity

Main idea: bring all the multi-modal inputs to one modality, namely text.



Case study 1: MLLMs and video popularity

Outcome: prompting an MLLM works better than training a modal specifically to solve the task at hand, with explainability as a bonus.

Video content



Title: Mexico vs. Brazil Highlights | International Friendly

Text summary

The video starts with Brazil attacking. Andreas Pereira scores a goal for Brazil after Mexico's Edson Alvarez dives in

retrieved videos



LLM hypothesis

1. highlight intense matches, finals, or close games
2. feature well-known or popular teams/players

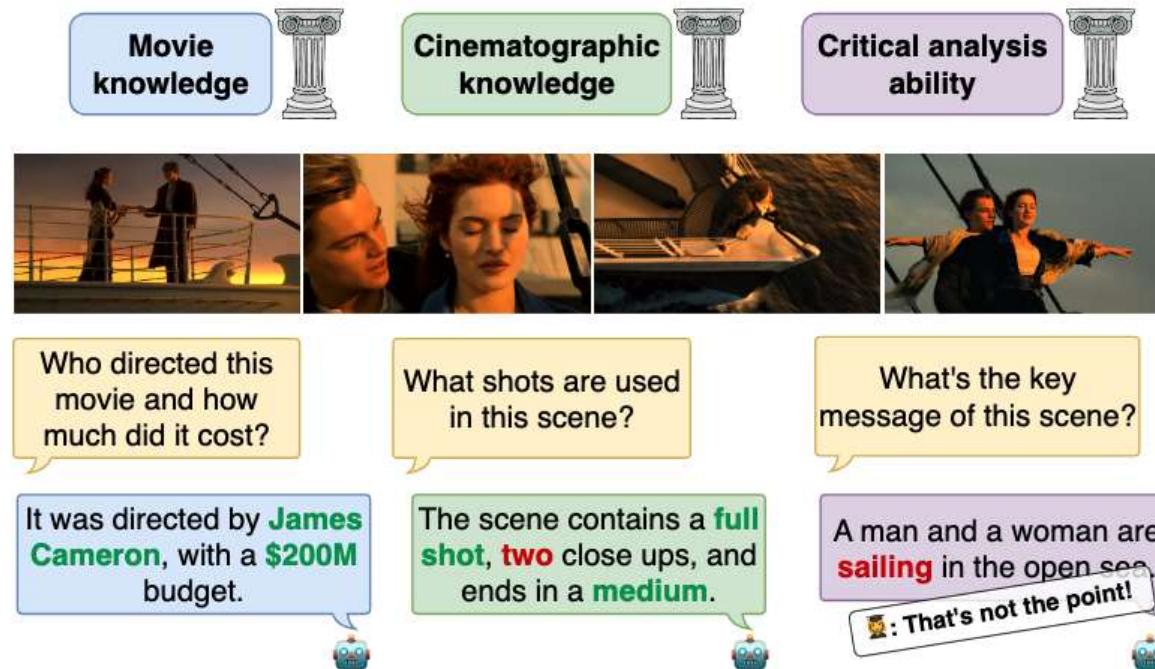
Prediction : 4 / 4

LLM explanation

1. The match is between Brazil and Mexico, Brazil being one of the biggest national teams in the world.
2. The video features several star players including Vinicius and Richarlison.

Case study 2: MLLMs and movies

Are MLLMs Movie Buffs? No.



"Are Multimodal LMMs Movie Buffs." Brett et al. under review.

Case study 2: MLLMs and movies

MLLMs are decent at predicting meta-categories and basic cinematographics.



GT: Action, Adventure, Sci-Fi
Pred: Action, Adventure, Sci-Fi



GT: 100M+ USD
Pred: 10-50M USD



GT: Extreme close-up
Pred: Extreme close-up



GT: Close-up
Pred: Extreme close-up

But did they get this from viewing the visuals, or because the LLM scanned IMDb?

Case study 2: MLLMs and movies

We can ask the MLLM to act as a film studies student. Then we can give its output to a film studies teacher to evaluate.



[...] The scene begins with a close-up of a woman lying on an operating table, wearing a hospital gown and an oxygen mask. The camera then pans out to reveal a group of surgeons dressed in surgical gowns, masks, and caps, preparing for the operation. The lighting is dim, with a blue hue dominating the scene, creating a clinical and sterile atmosphere. [...]



Incorrect, the first scene is a full shot of the whole group.

Accurate comment on the lighting!

No comments on the fact that she's flying and the surgeons turn into aliens?



The use of shadows and low lighting creates an atmosphere of suspense [...] The camera angles are carefully chosen to emphasize the power dynamics at play, with the man in the suit often positioned higher than the police officer. [...] The use of slow motion during key moments adds to the dramatic effect [...]



Comments on lighting and tone are accurate.

Good assessment of the power dynamics based on positioning!

There is no slow motion.



Conclusion: MLLMs don't really use the visual modality and hallucinate everything.

Looking beyond CLIP

In CLIP, the text encoder is learnt from scratch, why not start from an LLM?

How to efficiently fine-tune VLMs?

What about other modalities?

CLIP is flat, but the real-world is hierarchical. How can we fix this?

Next lecture

Lecture	Title	Lecture	Title
1	Intro and history of deep learning	2	AutoDiff
3	Deep learning optimization I	4	Deep learning optimization II
5	Convolutional deep learning	6	Attention-based deep learning
7	Graph deep learning	8	From supervised to unsupervised deep learning
9	Multi-modal deep learning	10	Generative deep learning
11	What doesn't work in deep learning	12	Non-Euclidean deep learning
13	Q&A	14	Deep learning for videos

Learning and reflection

Multi-modal deep learning not covered in Understanding Deep Learning book.

Thank you