Vision-Language Models

Part II:

VLMs using LLMs

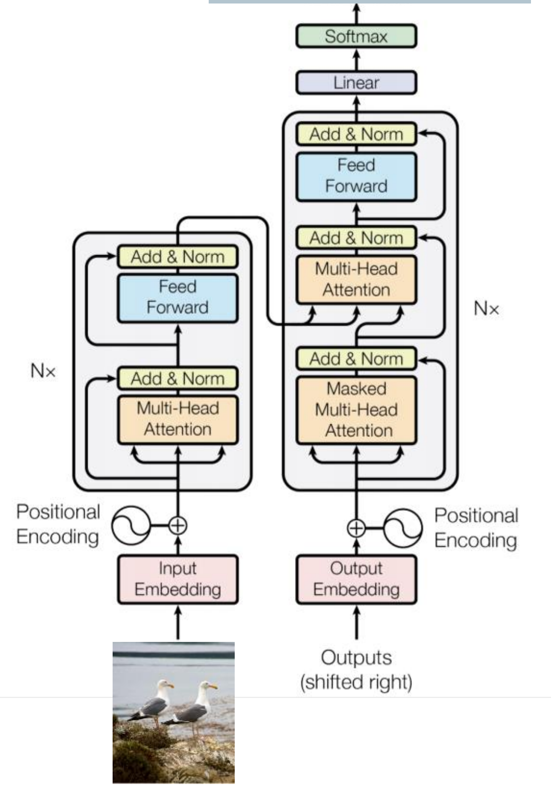
Outline

1. **Vision-Language Models in the era of LLMs**

   - Unimodal models with connection

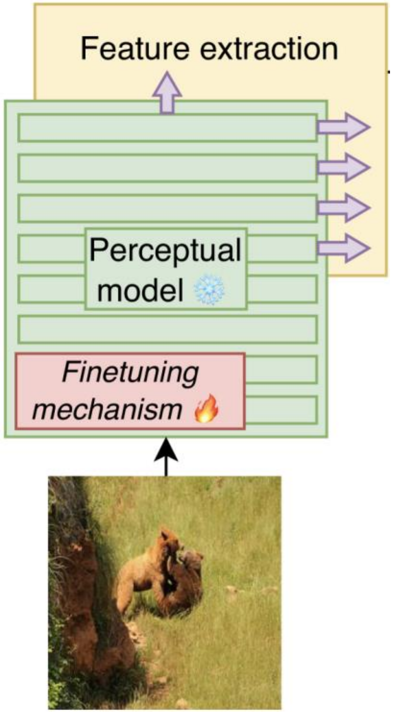
   - One model for all

Here are two sparrows on the beach at low tide



Vision Encoder + LLM Decoder

Image as input, textual caption as output



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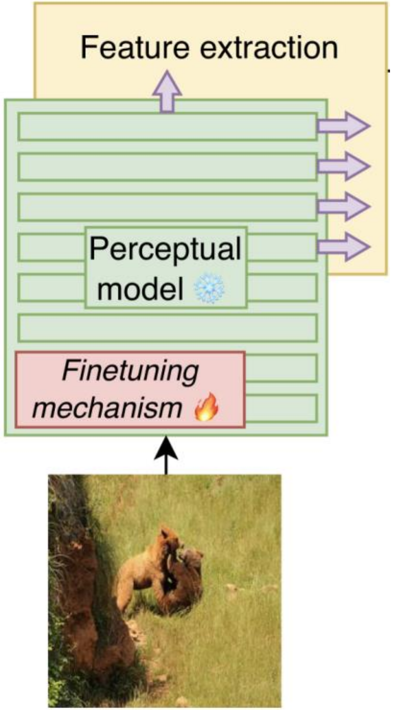

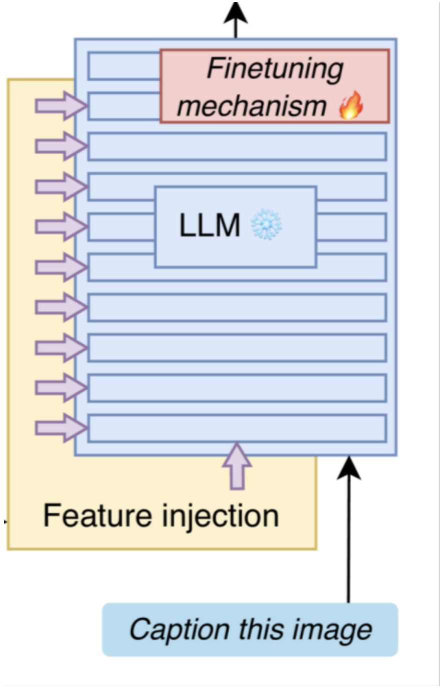

Vision Encoder + LLM Decoder

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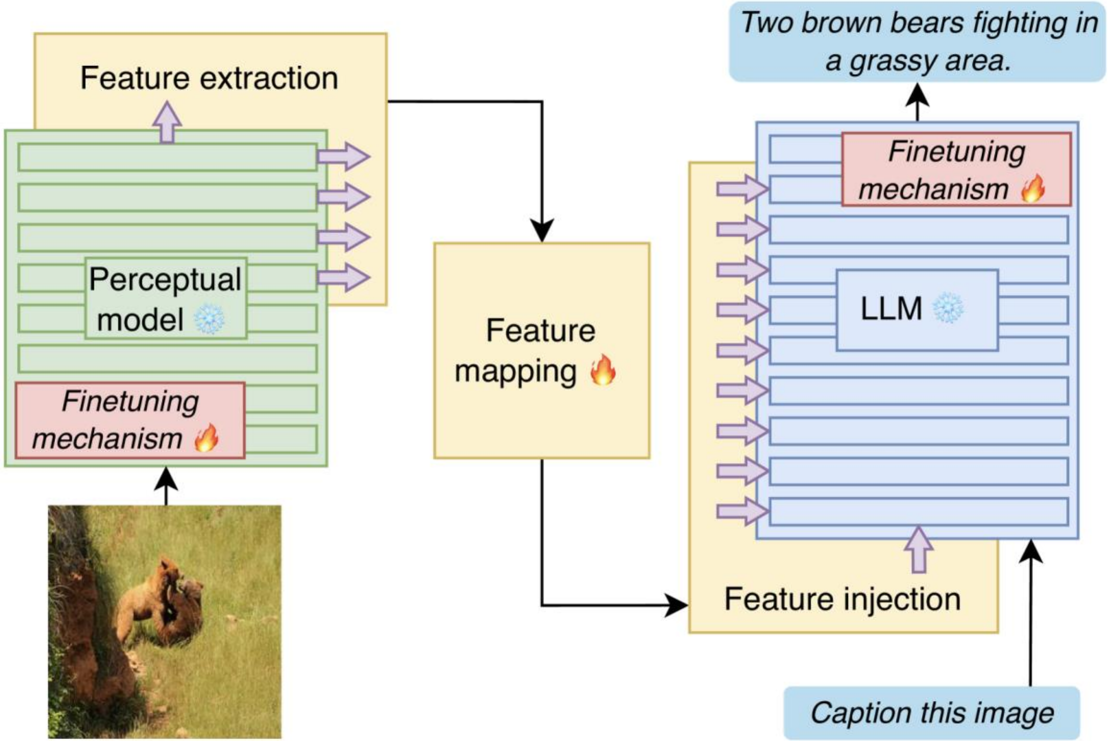
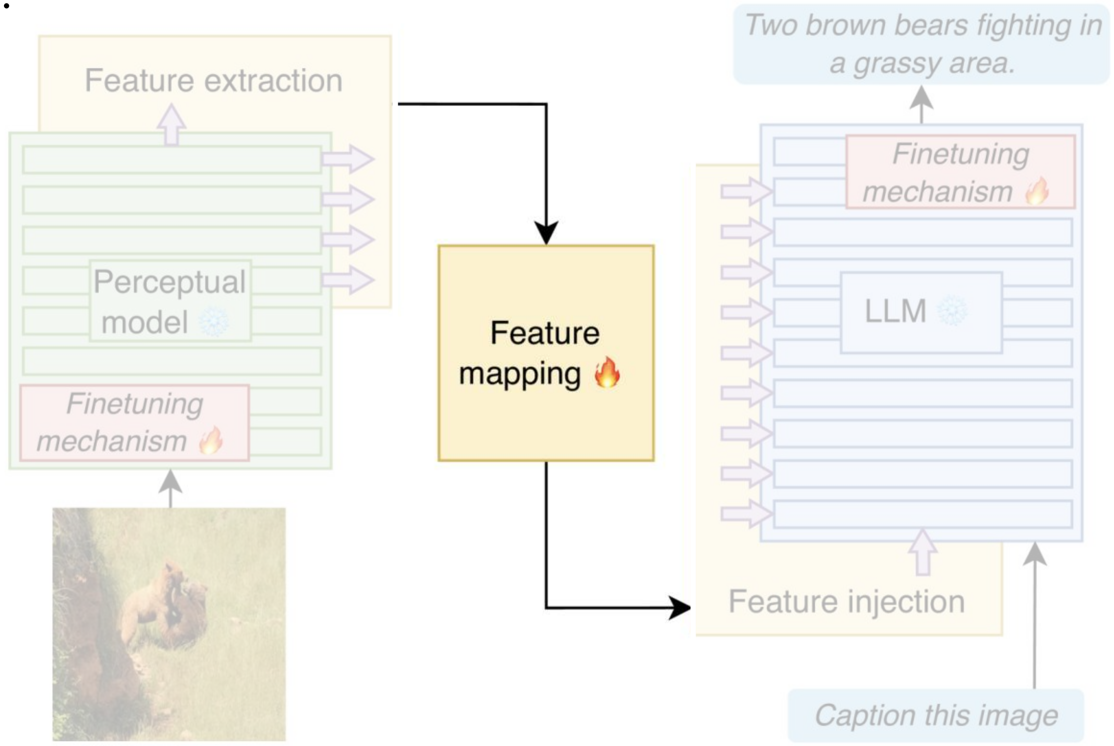


Why this modeling? Because the best LLM ever designed (and the plug&play update if a new LLM is released)

Vision Encoder + LLM Decoder

Feature mapping module?
A classic MLP, or:

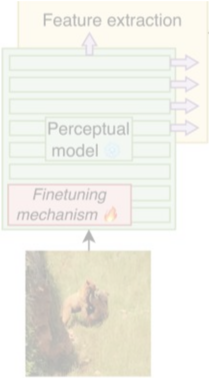


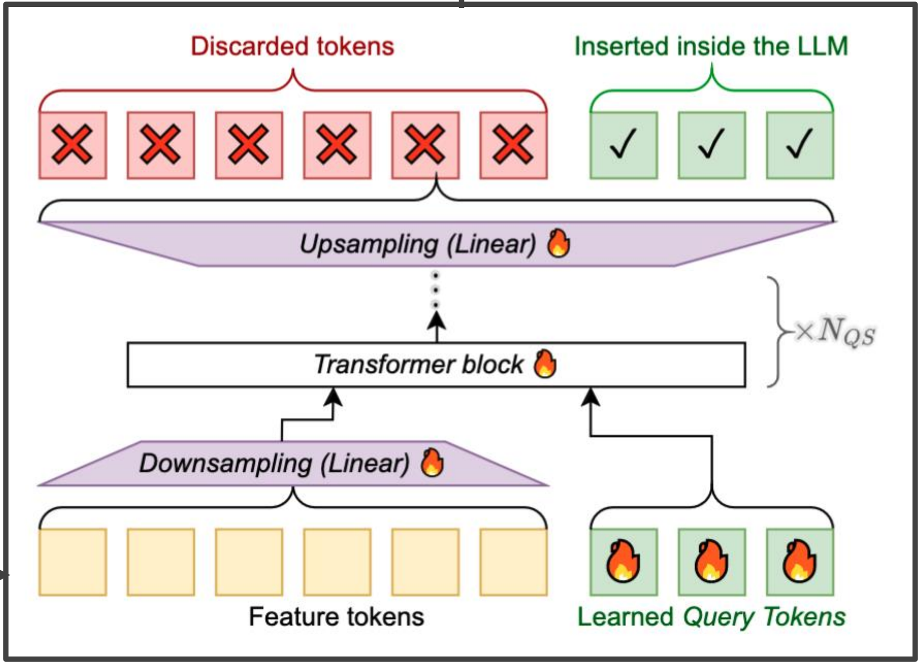
Vision Encoder + LLM Decoder

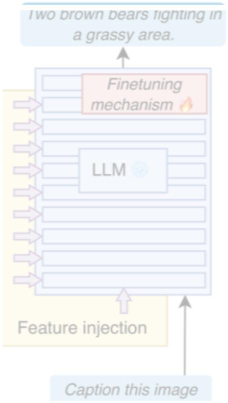
Feature mapping module?

A classic MLP,

Or ViT like with extra tokens

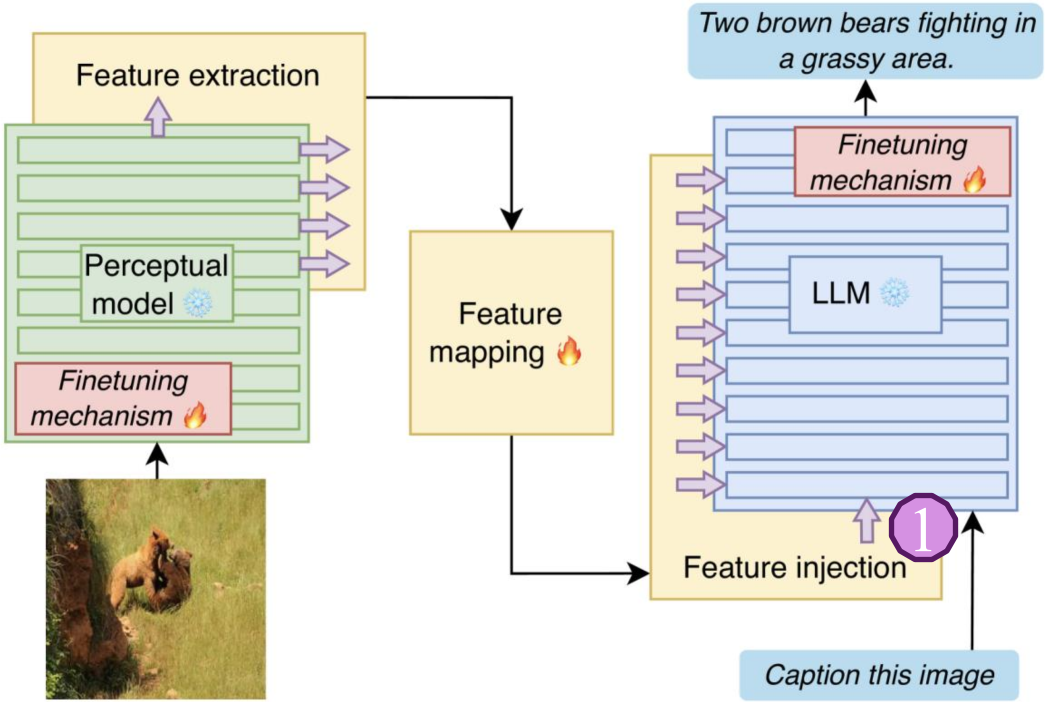






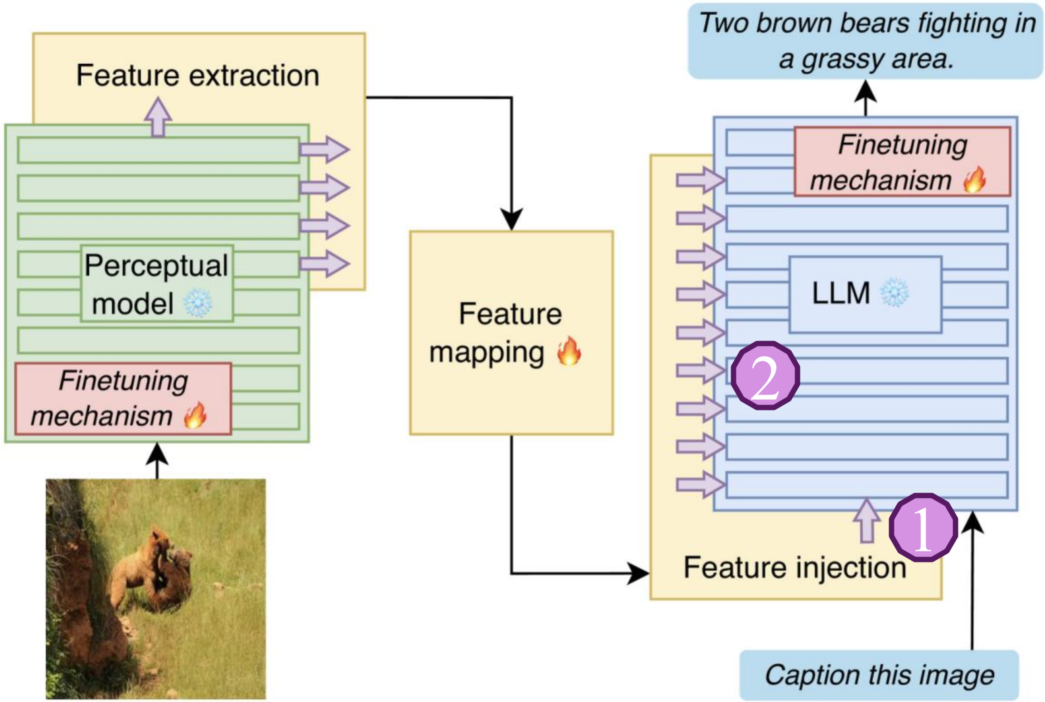
Vision Encoder + LLM Decoder

After feature mapping, feature **injection**!



Vision Encoder + LLM Decoder

After feature mapping, feature **injection**!



input: img
output: text caption

img → visual CLIP encoder * → features extraction (from last CLIP layer or n last layers)

↓

FEATURE MAPPING *

↓

feature injection → LLM * → caption
(it can be before the LLM or in the cross-attention of intermediate blocks)

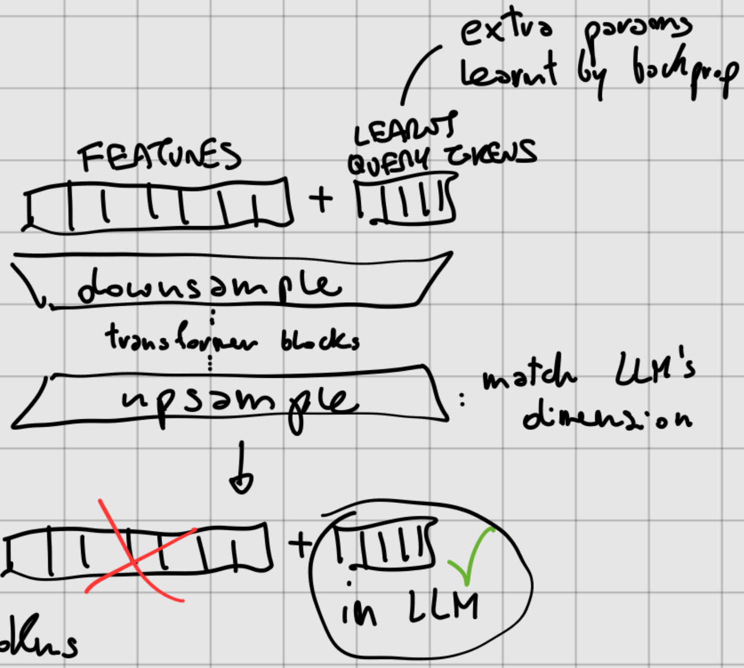
prompt: "add a caption" →

* frozen
* fine tuning

Another model that learns a mapping:

ViT with extra tokens :
(or MLP)

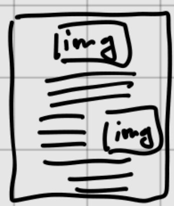
← to match : transformer's dimension



In classification we add a CLS token for the head, same thing for the added query tokens
(to pull all the visual information towards the added tokens)

Vision encoder + LLM decoder can be modified in any step:

- ideal: froze LLM, backbone
  train mapping in a limited training set
- many unimodal models → multimodal
- build a huge multimodal dataset → to scale (Billions)
- train (vision encoder → mapping → visual tokens + text → LLM)
- works very well when the output is text

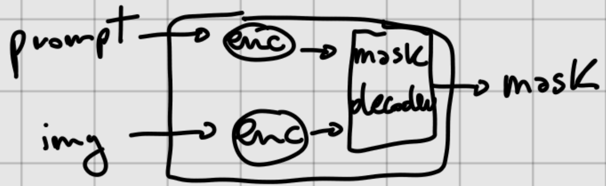


or OFA (One For All)
4M (Massively Multimodal Masked Modeling)

any input → any output

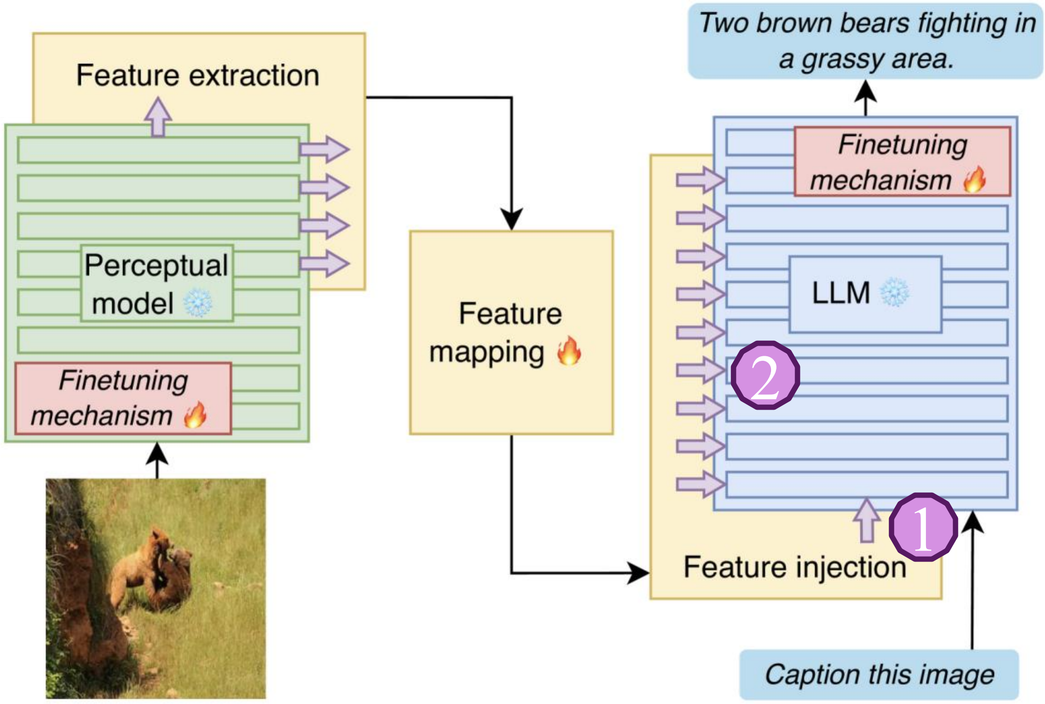
composed by many models that can solve many tasks

like SAM (Segment Anything Model)



Vision Encoder + LLM Decoder

After feature mapping, feature **injection**!



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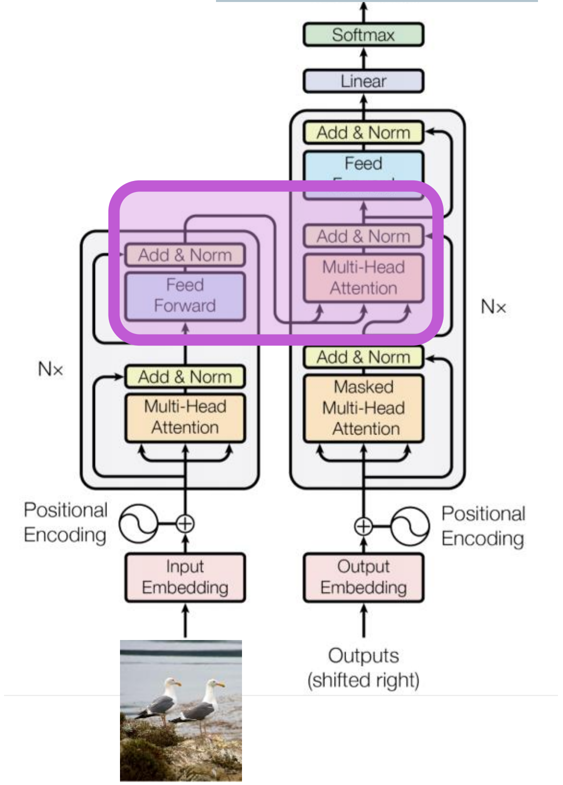
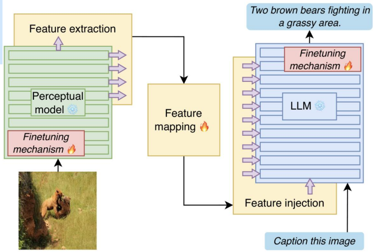
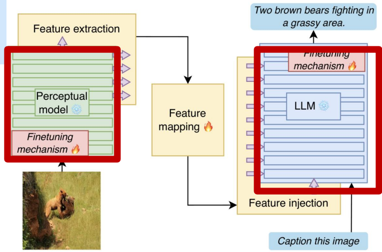


Vision Encoder + LLM Decoder



Method	Backbones		Adaptation mechanism				# Tr.
	LLMs	Perceptual Enc.	Feature extraction	Feature mapping	Feature injection	Fine-tuning mechanisms	params.
Flamingo [1]	Chinchilla [33]	NFNet [5]	Tokens from last layer	Perceiver Resampler (Transformer)	GATED XATTN-DENSE (Cross-attention)	–	10B
BLIP-2 [43]	OPT [92], FlanT5 [13]	CLIP [65]	Tokens from last layer	Q-Former	1st layer token injection	–	1.2B
MAGMA [22]	GPT-J 6B [86]	CLIP [65] / NFNet [5]	Tokens from last layer	MLP	1st layer token injection	fine-tuning of perceptual model	243M
MAPL [58]	GPT-J 6B [86]	CLIP-L [65]	Tokens from last layer	QPMapper (d_{embed}=256, 4 layers)	1st layer token injection	–	3.4M
PromptFuse [46]	BART [42]	ViT [19]	Tokens from last layer	*nothing*	–	prompt tuning	15K
LiMBeR [60]	GTP-J 6B [86]	CLIP [65]	Tokens from last layer	Linear projection	1st layer token injection	–	12.5M
eP-ALM [72]	OPT-2.7B/6.7B [92]	ViT [77], AST [27], TimeSformer [4]	CLS tokens from n last layers	(Shared) linear projection	Token injection in intermediate layers	prompt tuning	4.2M
LLaMA-Adapter [25, 91]	LLaMA[82]	CLIP [65]	Tokens from last layer	Linear projection	Token injection in intermediate layers	inner-layer prompt tuning, bias tuning, norm tuning	14M
Frozen [84]	GPT-like [66]	NFNet [5]	Pooled output tokens	*nothing*	1st layer token injection	Fine-tune the NFNet	40.3M
ClipCap [61]	GPT-2[66]	CLIP [65]	Tokens from last layer	Transformer	1st layer token injection	–	43M
VL-Adapter [79]	BART [42], T5 [67]	CLIP [65]	Tokens from last layer	Linear projection	1st layer token injection	Adapters	5.8M
AnyMAL [62]	Llama 2-70B-chat [83],	CLIP [65], CLAP [23]	Tokens from last layer	Perceiver Resampler, or linear projection	1st layer token injection	LoRA [34]	–
DePALM$^{\text{QP,inner}}$	OPT-6.7B [92], LLaMA [82]	CLIP-L [65], DINOv2 [63], MAViL [36] TimeSformer [4]	Tokens from n last layers	QPMapper	Token injection in intermediate layers	prompt tuning	18.1M
DePALM			Tokens from last layer		1st layer token injection		17.9M
DePALM$^{\text{R-rand,L0}}$, DePALM$^{\text{R-linear,L0}}$, DePALM$^{\text{R-QPMapper,L0}}$, DePALM$^{\text{R-avgpool,L0}}$				Linear projection + Resampler			21M, 88M 18M, 21M
DePALM$^{\text{c-attn}}$			Tokens from n last layers	Projection + Small Transformer	Gated cross-attention		17.9M

Vision Encoder + LLM Decoder



Method	Backbones: LLMs	Backbones: Perceptual Enc.	Adaptation mechanism: Feature extraction	Adaptation mechanism: Feature mapping	Adaptation mechanism: Feature injection	Adaptation mechanism: Fine-tuning mechanisms	# Tr. params.
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MAGMA [22]	GPT-J 6B [86]	CLIP [65] / NFNet [5]	Tokens from last layer	MLP	1st layer token injection	fine-tuning of perceptual model	243M
MAPL [58]	GPT-J 6B [86]	CLIP-L [65]	Tokens from last layer	QPMapper (d_{embed}=256, 4 layers)	1st layer token injection	–	3.4M
PromptFuse [46]	BART [42]	ViT [19]	Tokens from last layer	*nothing*	–	prompt tuning	15K
LiMBeR [60]	GTP-J 6B [86]	CLIP [65]	Tokens from last layer	Linear projection	1st layer token injection	–	12.5M
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Frozen [84]	GPT-like [66]	NFNet [5]	Pooled output tokens	*nothing*	1st layer token injection	Fine-tune the NFNet	40.3M
ClipCap [61]	GPT-2[66]	CLIP [65]	Tokens from last layer	Transformer	1st layer token injection	–	43M
VL-Adapter [79]	BART [42], T5 [67]	CLIP [65]	Tokens from last layer	Linear projection	1st layer token injection	Adapters	5.8M
AnyMAL [62]	Llama 2-70B-chat [83],	CLIP [65], CLAP [23]	Tokens from last layer	Perceiver Resampler, or linear projection	1st layer token injection	LoRA [34]	–
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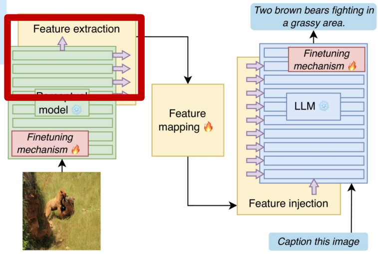
DePALM$^{\text{c-attn}}$			Tokens from n last layers	Projection + Small Transformer	Gated cross-attention		17.9M

Vision Encoder + LLM Decoder



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PromptFuse [46]	BART [42]	ViT [19]	Tokens from last layer	*nothing*	–	prompt tuning	15K
LiMBeR [60]	GTP-J 6B [86]	CLIP [65]	Tokens from last layer	Linear projection	1st layer token injection	–	12.5M
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Frozen [84]	GPT-like [66]	NFNet [5]	Pooled output tokens	*nothing*	1st layer token injection	Fine-tune the NFNet	40.3M
ClipCap [61]	GPT-2[66]	CLIP [65]	Tokens from last layer	Transformer	1st layer token injection	–	43M
VL-Adapter [79]	BART [42], T5 [67]	CLIP [65]	Tokens from last layer	Linear projection	1st layer token injection	Adapters	5.8M
AnyMAL [62]	Llama 2-70B-chat [83],	CLIP [65], CLAP [23]	Tokens from last layer	Perceiver Resampler, or linear projection	1st layer token injection	LoRA [34]	–
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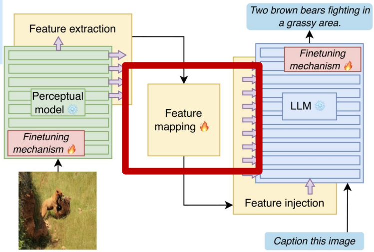
DePALM$^{\text{c-attn}}$			Tokens from n last layers	Projection + Small Transformer	Gated cross-attention		17.9M

Vision Encoder + LLM Decoder



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DePALM$^{\text{R-rand,L0}}$, DePALM$^{\text{R-linear,L0}}$, DePALM$^{\text{R-QPMapper,L0}}$, DePALM$^{\text{R-avgpool,L0}}$			Tokens from last layer	Linear projection + Resampler	1st layer token injection		21M, 88M 18M, 21M
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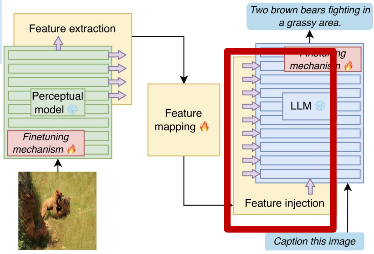

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DePALM			Tokens from last layer		1st layer token injection		17.9M
DePALM$^{\text{R-rand,L0}}$, DePALM$^{\text{R-linear,L0}}$, DePALM$^{\text{R-QPMapper,L0}}$, DePALM$^{\text{R-avgpool,L0}}$				Linear projection + Resampler			21M, 88M 18M, 21M
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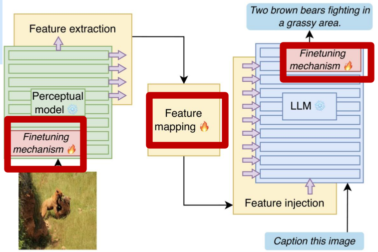

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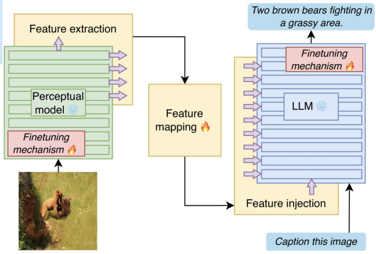
VL-Adapter [79]	BART [42], T5 [67]	CLIP [65]	Tokens from last layer	Linear projection	1st layer token injection	Adapters	5.8M
AnyMAL [62]	Llama 2-70B-chat [83],	CLIP [65], CLAP [23]	Tokens from last layer	Perceiver Resampler, or linear projection	1st layer token injection	LoRA [34]	–
DePALM$^{\text{QP,inner}}$	OPT-6.7B [92], LLaMA [82]	CLIP-L [65], DINOv2 [63], MAViL [36] TimeSformer [4]	Tokens from n last layers	QPMapper	Token injection in intermediate layers	prompt tuning	18.1M
DePALM			Tokens from last layer		1st layer token injection		17.9M
DePALM$^{\text{R-rand,L0}}$, DePALM$^{\text{R-linear,L0}}$, DePALM$^{\text{R-QPMapper,L0}}$, DePALM$^{\text{R-avgpool,L0}}$				Linear projection + Resampler			21M, 88M 18M, 21M
DePALM$^{\text{c-attn}}$			Tokens from n last layers	Projection + Small Transformer	Gated cross-attention		17.9M

Vision Encoder + LLM Decoder



Parameter efficient approaches:

Leave the LLM and backbone frozen,

Train the mapping on (very) limited training sets to obtain very good results

Simple design choices works best!

ie. passing all perceptual tokens at the input to the LLM

compress perceptual to a few “summary tokens”

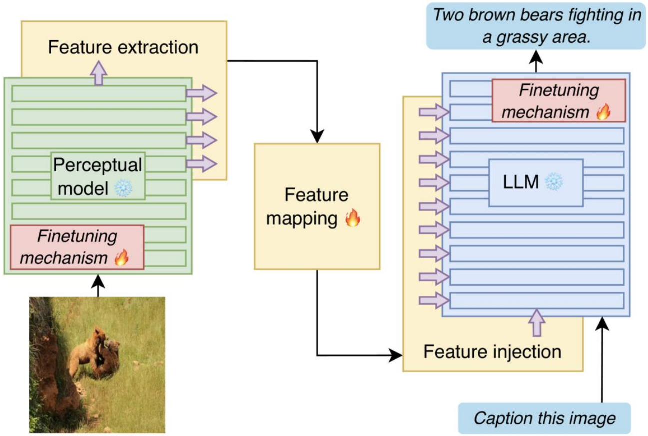
4 times faster to train and on par results

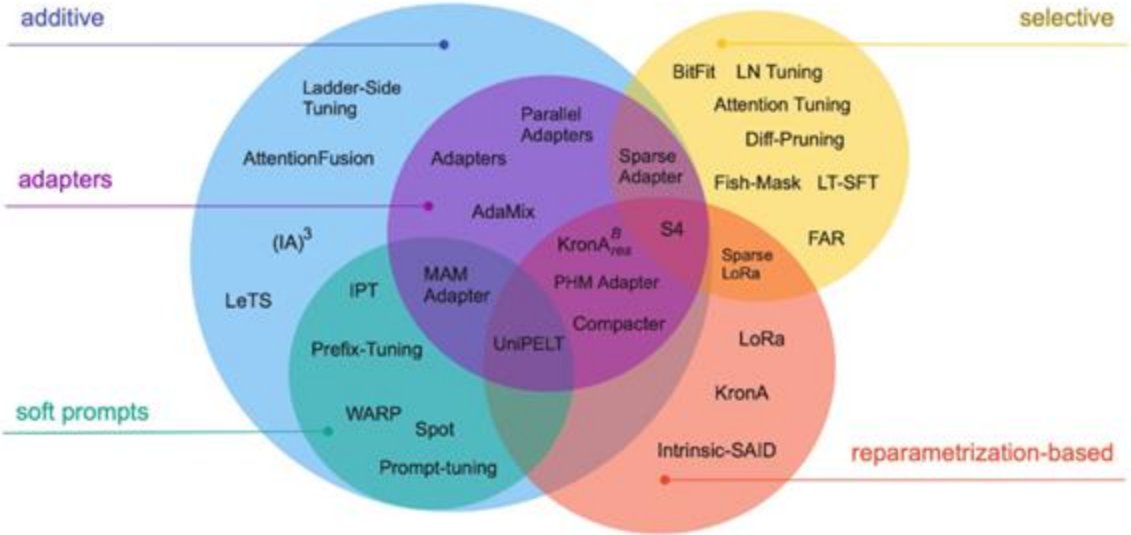
Vision Encoder + LLM Decoder

Many things to do on top of (pretrained) foundations models (if/when available)

Leverage **unimodal** models to build efficient **multimodal** models works well

Efficient finetuning: parameter efficiency, data efficiency, …





Vision Encoder + LLM Decoder

How to get the best VLM?

Relax the **efficiency** constraint

1/ Build a huge multimodal dataset

Vision Encoder + LLM Decoder

How to get the best VLM?

Relax the **efficiency** constraint

1/ Build a huge multimodal dataset

Image-Text Pairs

Tottenham vs Chelsea Live Streaming

Tottenham Spurs vs Chelsea Live Streaming

Multimodal Document

The match between Tottenham Spurs vs Chelsea will kick off from 16:30 at Tottenham Hotspur Stadium, London.

The derby had been played 54 times and the Blues have dominated the Spurs. Out of 54 matches played, Chelsea has won 28 times and Spurs had only won 7 times. The remaining 19 matches had ended in draw.

However, in recent 5 meetings, Spurs had won 3 times where Chelsea had won the other two times. …

+Add synthetized data …

Dataset	Images	% unique images	Docs	Tokens	Open
KOSMOS-1	-	-	71M	-	✗
M3W	185M	-	43M	-	✗
mmc4-ff	385M	60.6%	79M	34B	✓
mmc4	**585M**	-	103M	43B	✓
OBELICS	353M	**84.3%**	**141M**	**115B**	✓

Table 1: General statistics of OBELICS and the current largest alternatives.

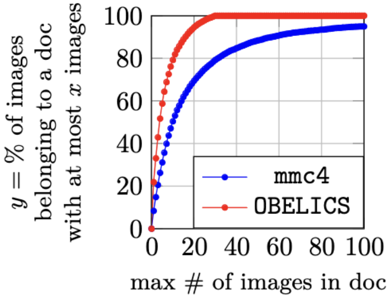
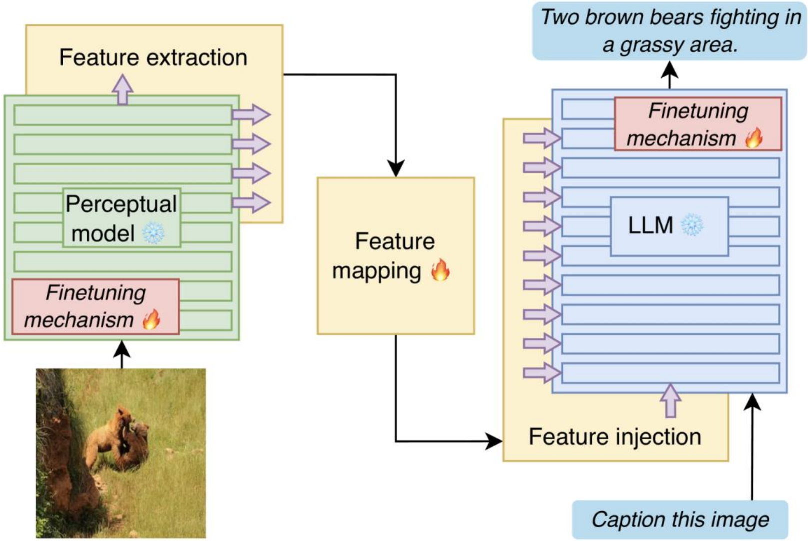


Figure 3: Distribution of images.

Vision Encoder + LLM Decoder

How to get the best VLM?
Relax the **efficiency** constraint
  1/ Build a huge multimodal dataset
  2/ Train your best model:



Best architecture?

Vision encoder
Feature Mapping to the LLM input space
Visual tokens (64 in our standard configuration)
interleaved with the input sequence of text embeddings
LLM

Vision Encoder + LLM Decoder

Evaluation very important, not easy for Generative models

Quantitative results:

Model	Size	Archi.	# tokens per image	VQAv2	TextVQA	OKVQA	COCO
OpenFlamingo	9B	CA	-	54.8	29.1	41.1	96.3
Idefics1	9B	CA	-	56.4	27.5	47.7	97.0
Flamingo	9B	CA	-	58.0	33.6	50.0	99.0
MM1	7B	FA	144	63.6	46.3	51.4	**116.3**
Idefics2-base	8B	FA	**64**	**70.3**	**57.9**	**54.6**	116.0

Qualitative results:

Prompt

Describe the image

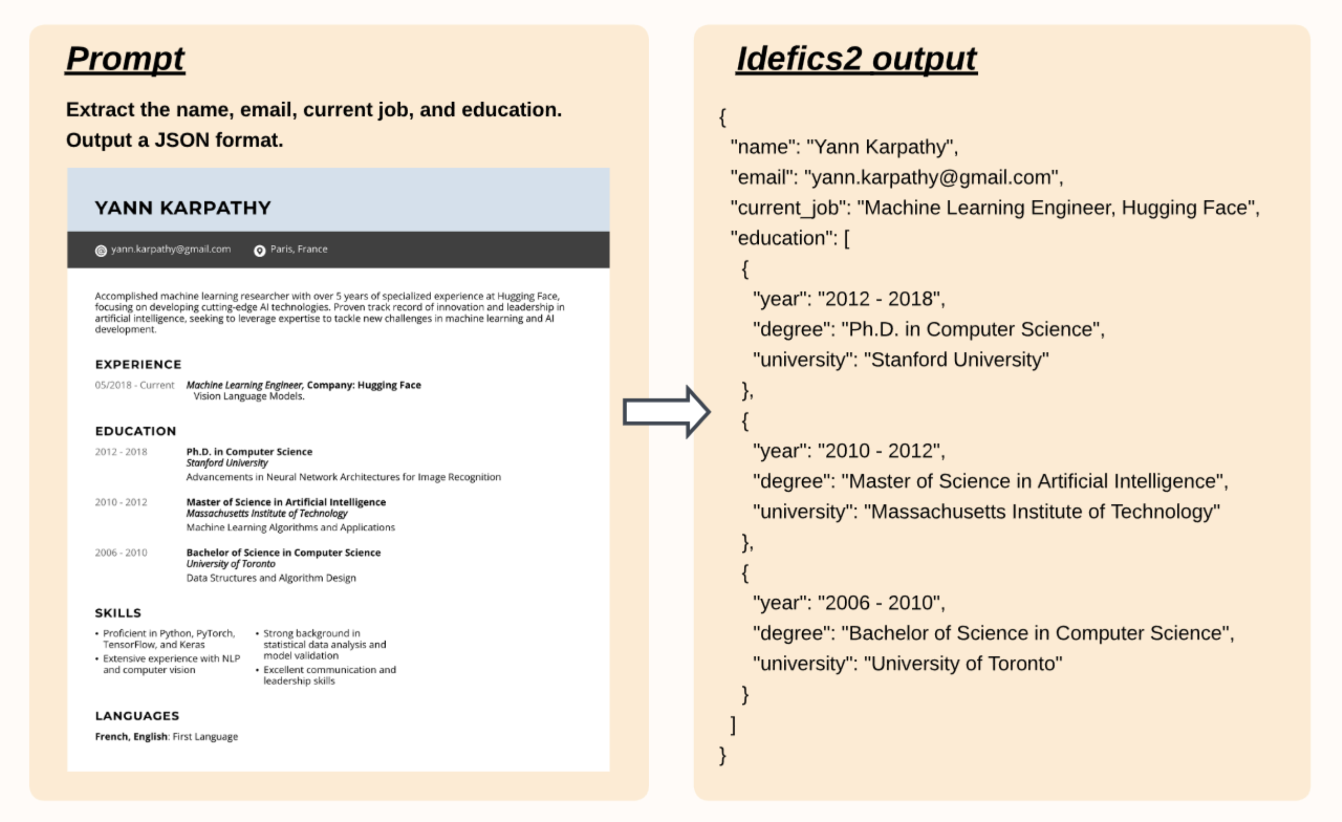
Idefics2 output

The image shows two golden retriever puppies sitting in a field of flowers. They are sitting next to each other, looking at the camera, and appear to be very happy. The puppies are adorable, and their fur is a beautiful golden color. The flowers surrounding them are yellow and add a vibrant touch to the scene.

Model	Size	# tokens per image	MMMU	MathVista	TextVQA	MMBench
LLaVA-NeXT	13B	2880	36.2/-	35.3	67.1	70.0
DeepSeek-VL	7B	576	36.6/-	36.1	64.4	73.2
MM1-Chat	7B	720	37.0/35.6	35.9	72.8	72.3
Idefics2	8B	**64**	**43.5/37.9**	**51.6**	70.4	**76.8**
Idefics2	8B	320	43.0/37.7	51.4	**73.0**	76.7

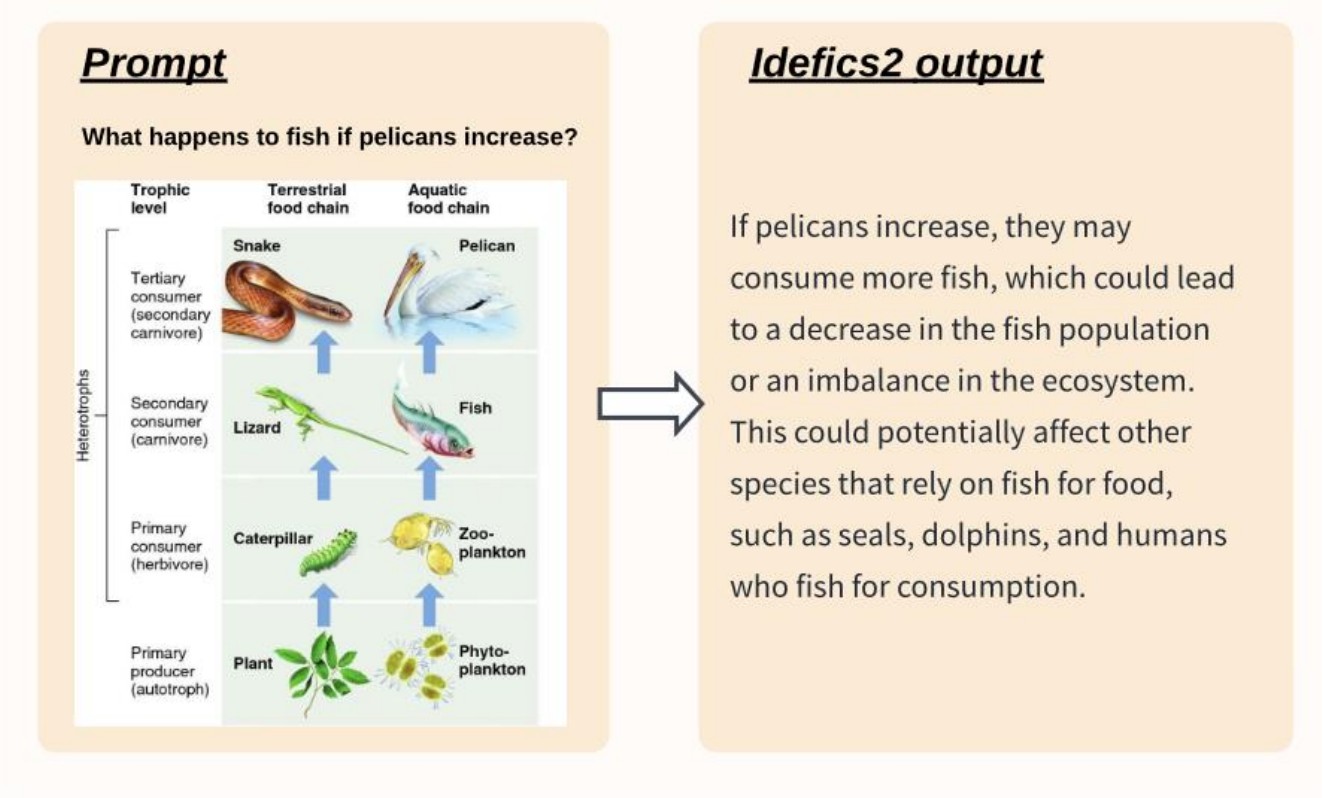
Vision Encoder + LLM Decoder

Qualitative results:

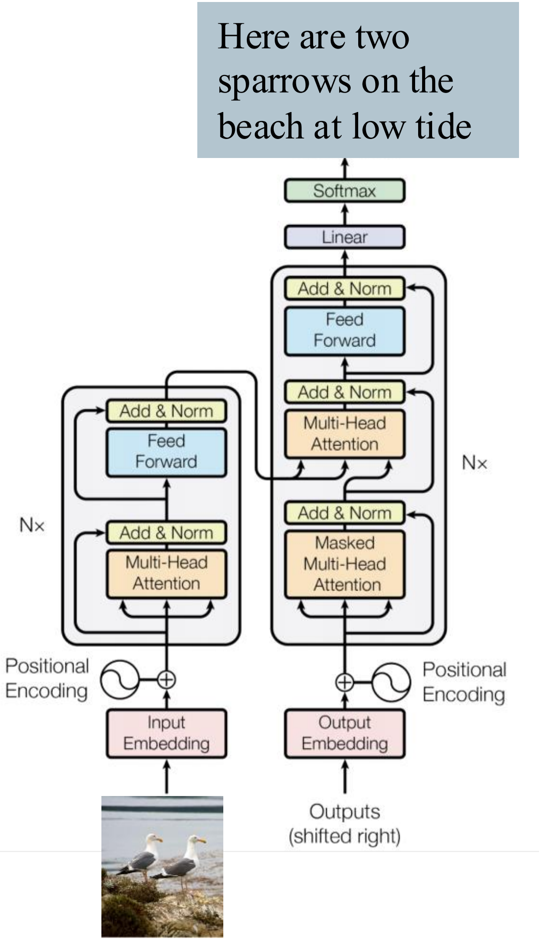


Vision Encoder + LLM Decoder

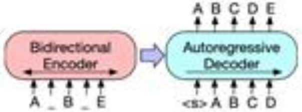
Qualitative results:



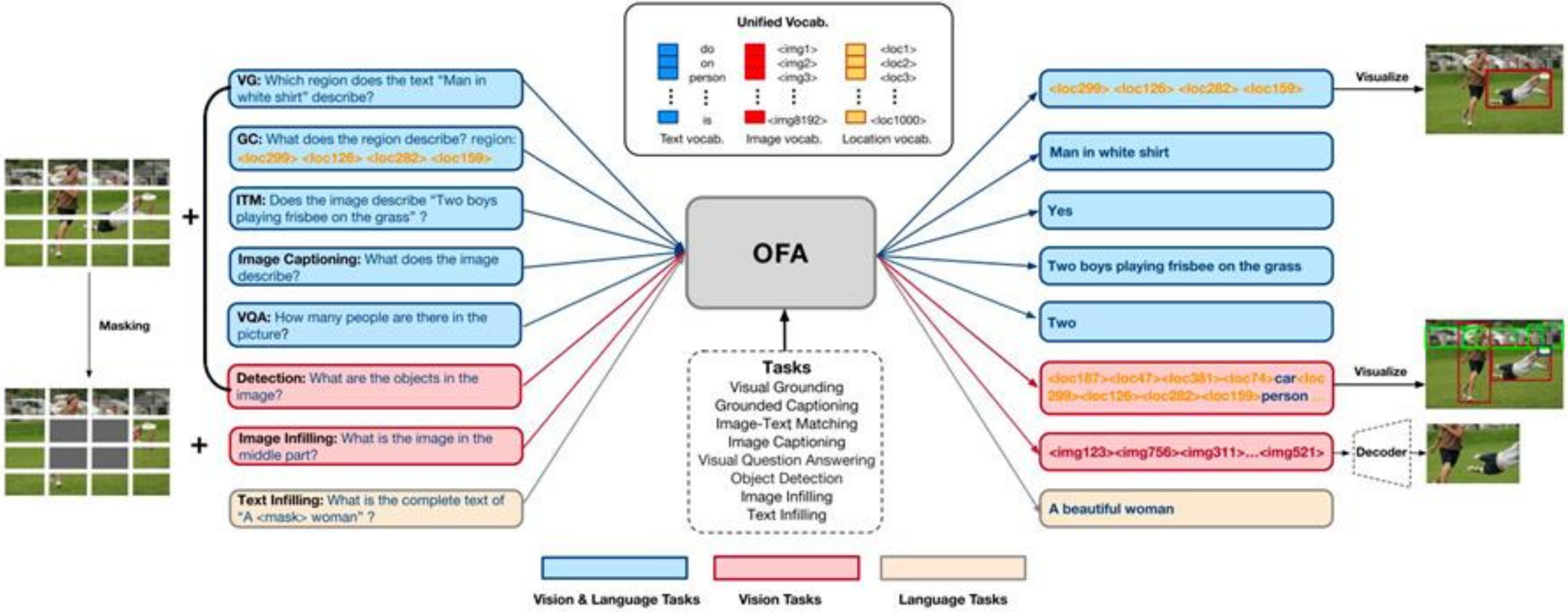
1. Vision-Language Models in the era of LLMs
   - Unimodal models with connection
   - **One model for all**



One model with:
many inputs / many outputs / many tasks



(c) BART: Inputs to the encoder need not be aligned with decoder outputs, allowing arbitary noise transformations. Here, a document has been corrupted by replacing spans of text with mask symbols. The corrupted document (left) is encoded with a bidirectional model, and then the likelihood of the original document (right) is calculated with an autoregressive decoder. For fine-tuning, an uncorrupted document is input to both the encoder and decoder, and we use representations from the final hidden state of the decoder.



NeurIPS 2023/24

4M: Massively Multimodal Masked Modeling

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Teresa Yeo[1] Mingfei Gao[2] Afshin Dehghan[2] Amir Zamir[1]
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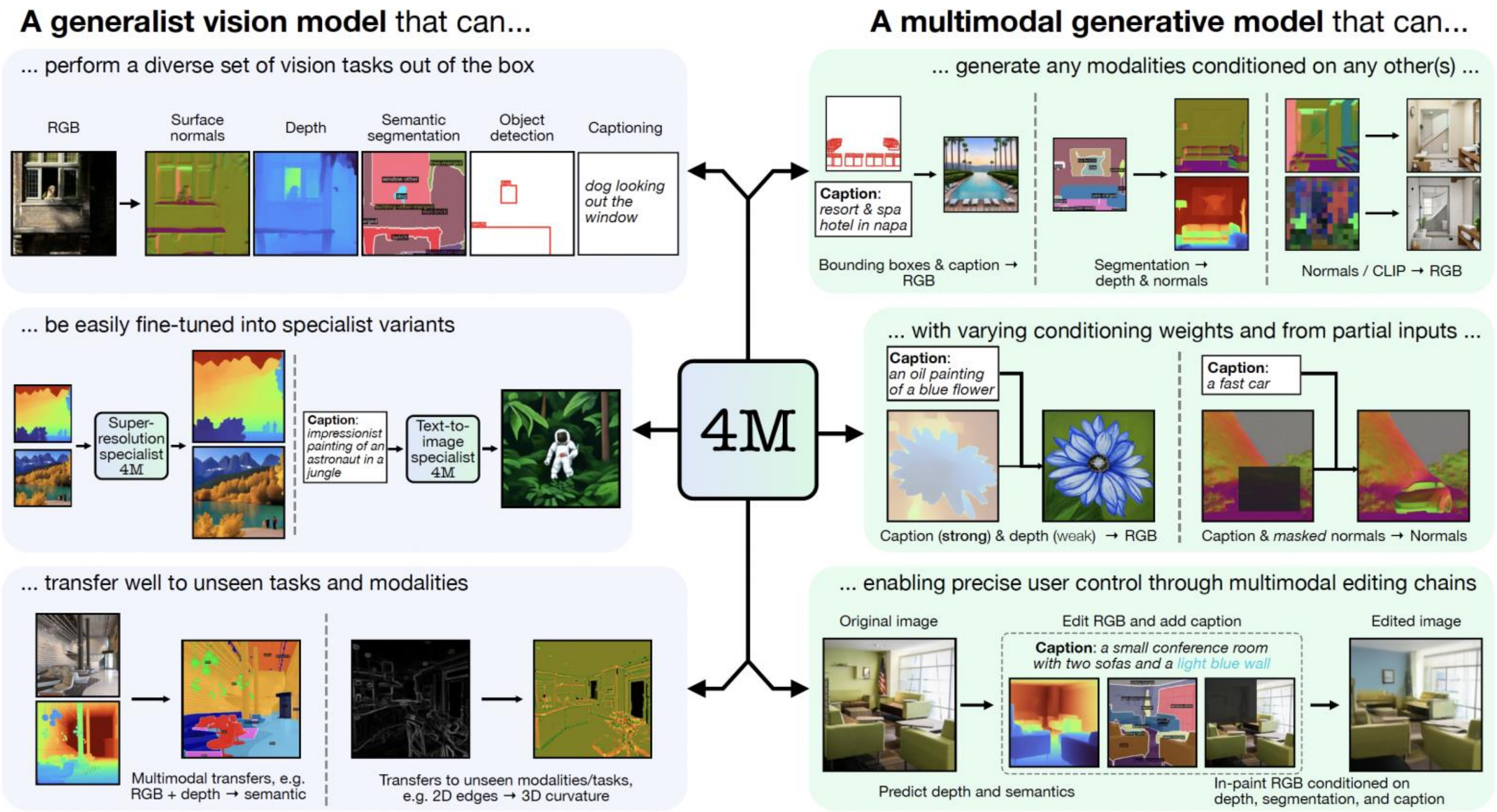
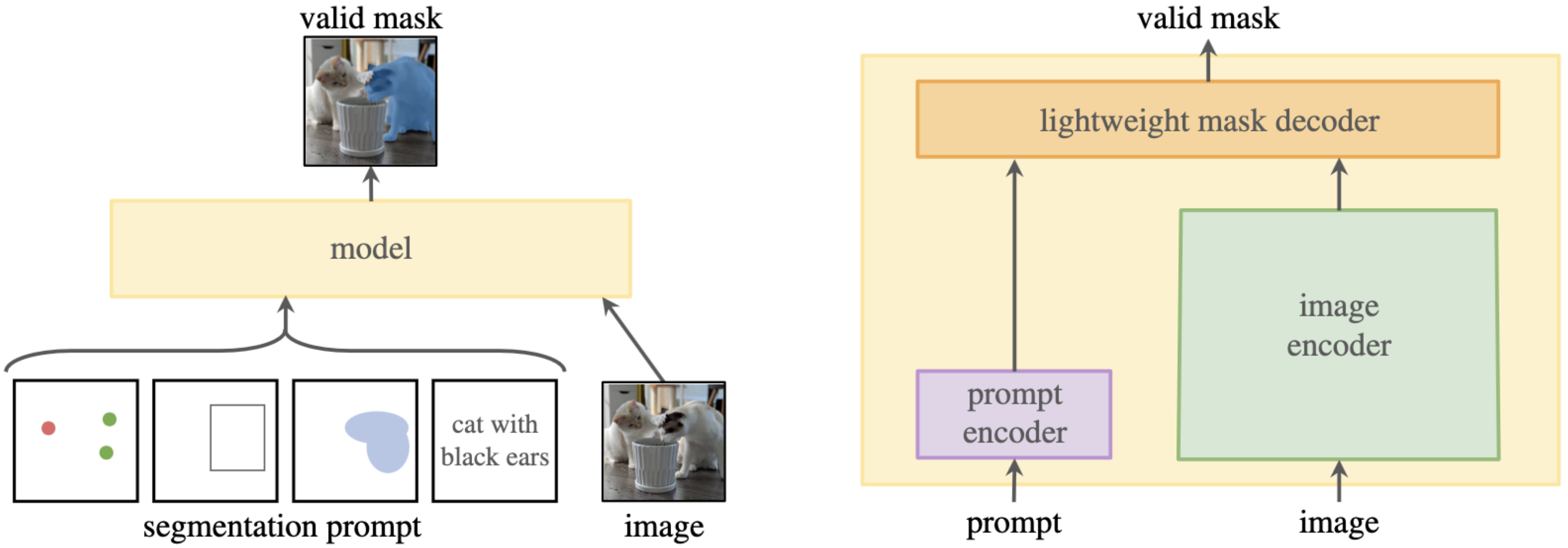


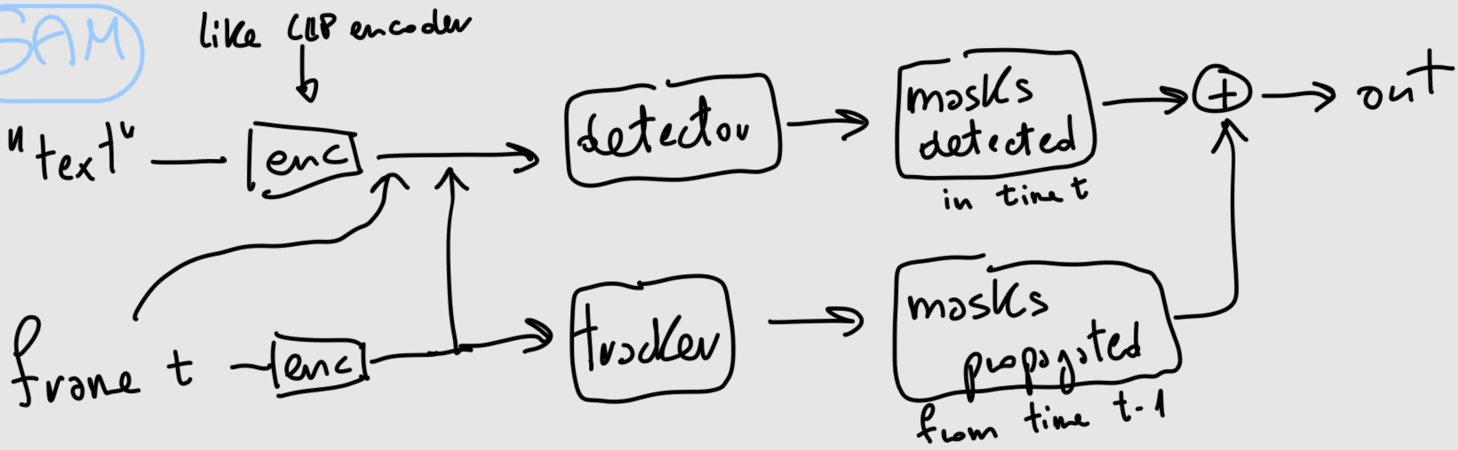
Segment Anything

Alexander Kirillov[1,2,4] Eric Mintun[2] Nikhila Ravi[1,2] Hanzi Mao[2] Chloe Rolland[3] Laura Gustafson[3]
Tete Xiao[3] Spencer Whitehead Alexander C. Berg Wan-Yen Lo Piotr Dollár[4] Ross Girshick[4]

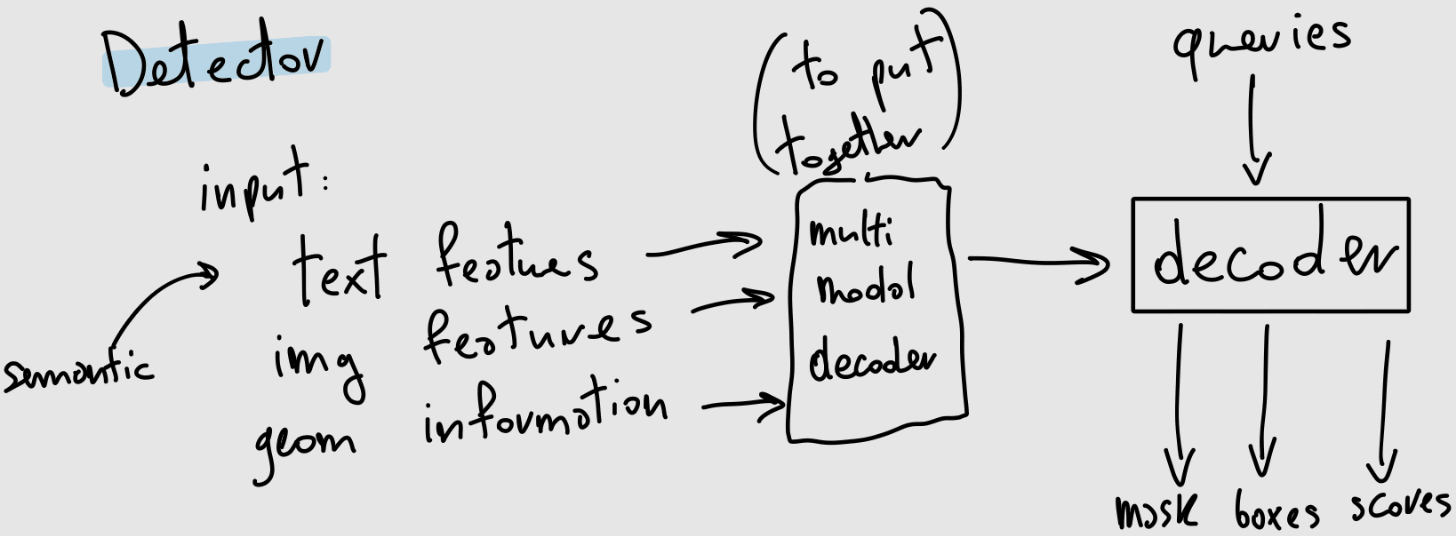


(a) **Task**: promptable segmentation (b) **Model**: Segment Anything Model (**SAM**)

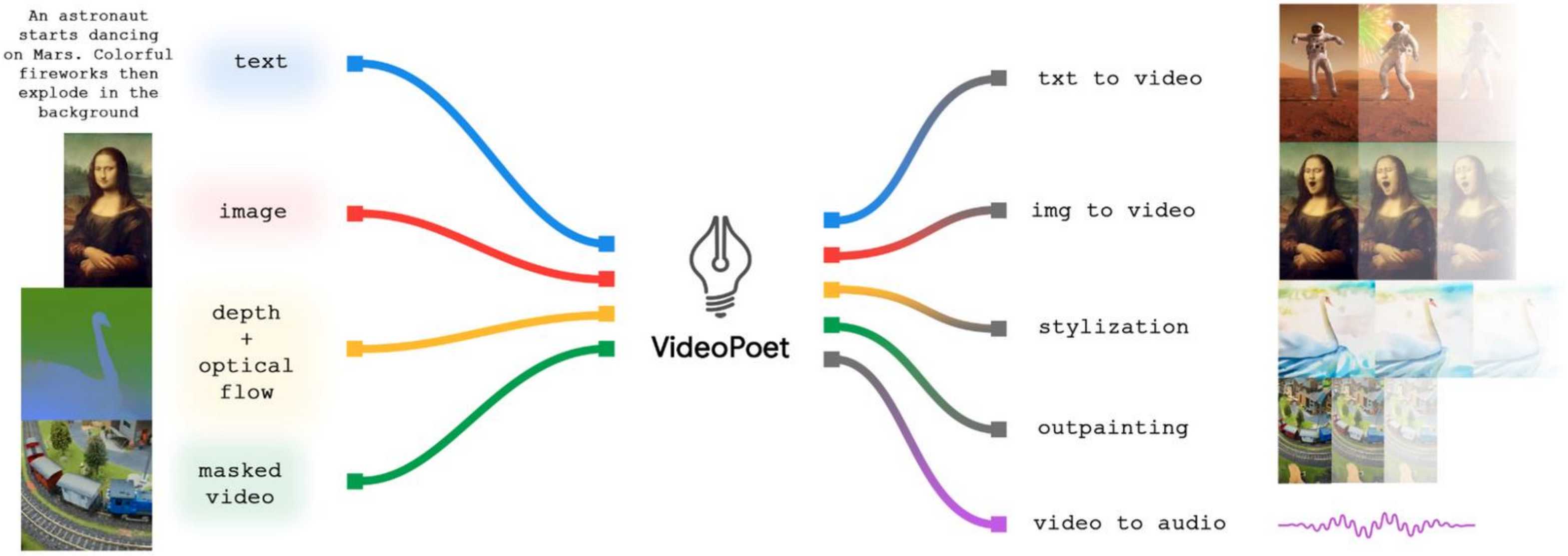
SAM



Detector

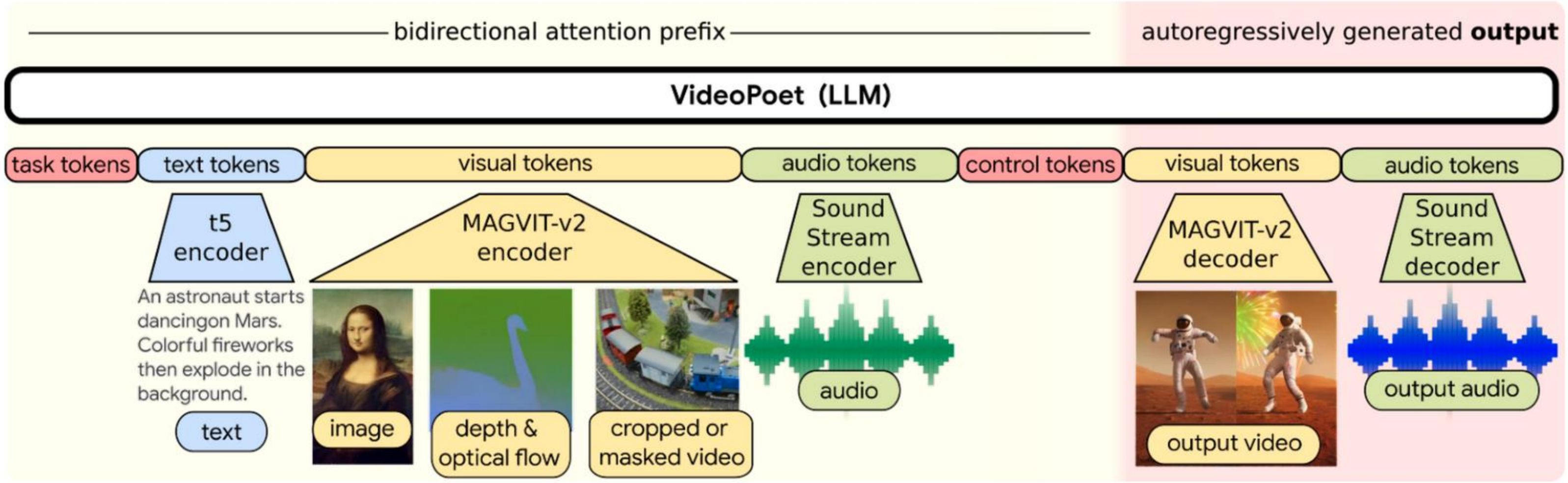


1M4all



*An overview of VideoPoet, capable of multitasking on a variety of video-centric inputs and outputs. The LLM can optionally take text as input to guide generation for text-to-video, image-to-video, video-to-audio, stylization, and outpainting tasks. Resources used: **Wikimedia Commons** and **DAVIS**.*

1M4all



A detailed look at the VideoPoet task design, showing the training and inference inputs and outputs of various tasks. Modalities are converted to and from tokens using tokenizer encoder and decoders. Each modality is surrounded by boundary tokens, and a task token indicates the type of task to perform.