Advancing Multimodal LLMs: From Seeing to Understanding and Acting

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CVPR | Apple | 2025.06.12

How VLMs were Trained A Decade Ago?

Show and Tell: A Neural Image Caption Generator

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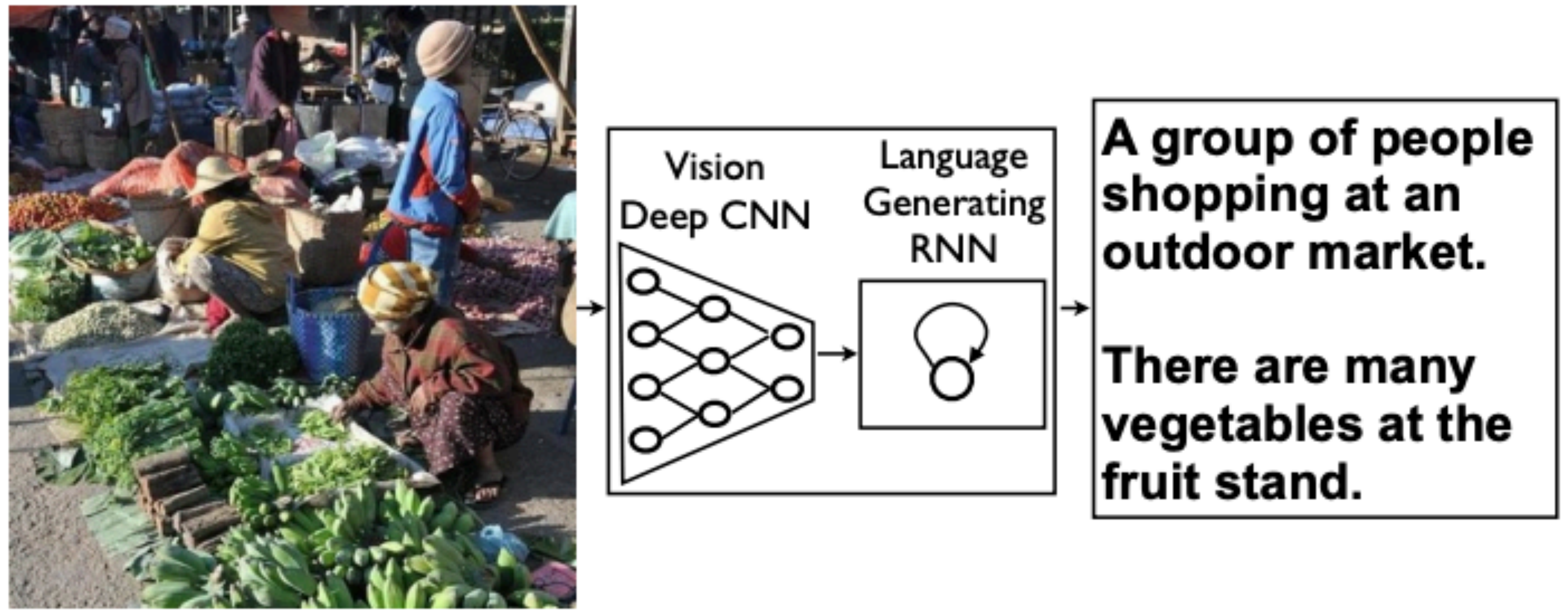

Figure 1. NIC, our model, is based end-to-end on a neural network consisting of a vision CNN followed by a language generating RNN. It generates complete sentences in natural language from an input image, as shown on the example above.

How VLMs are Trained Now?

Show and Tell: A Neural Image Caption Generator

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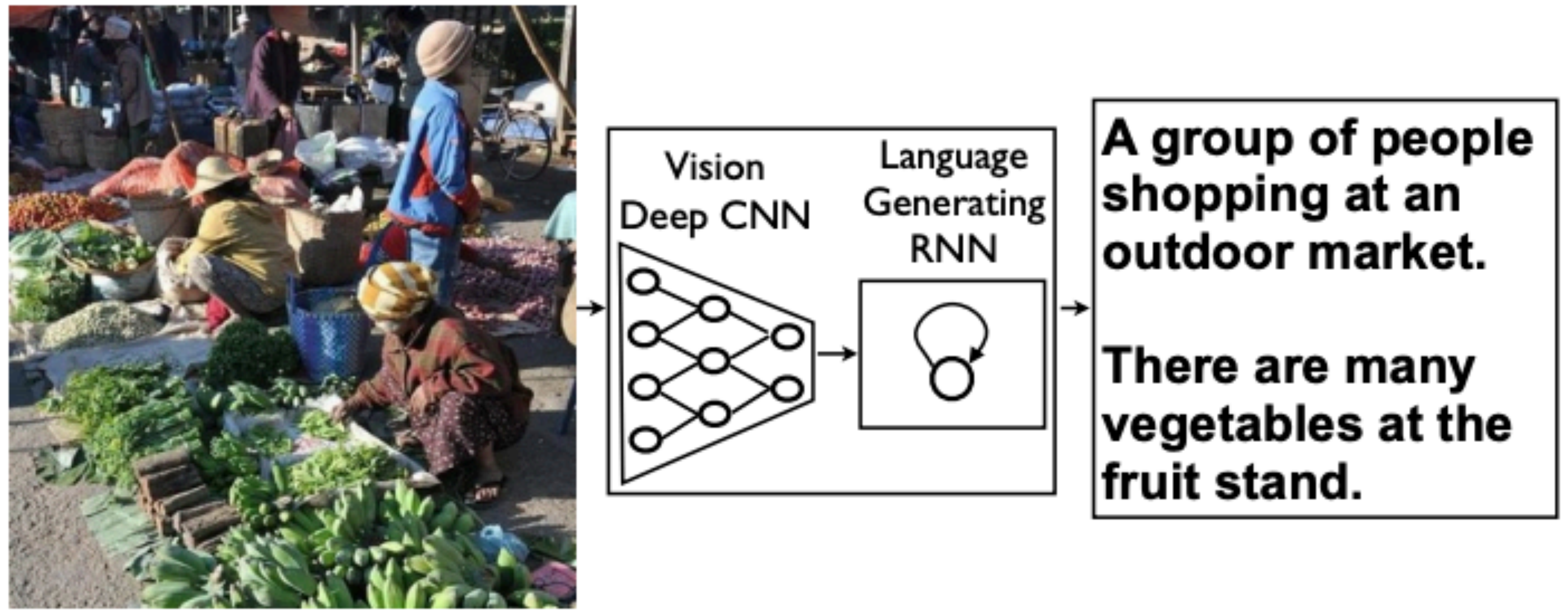

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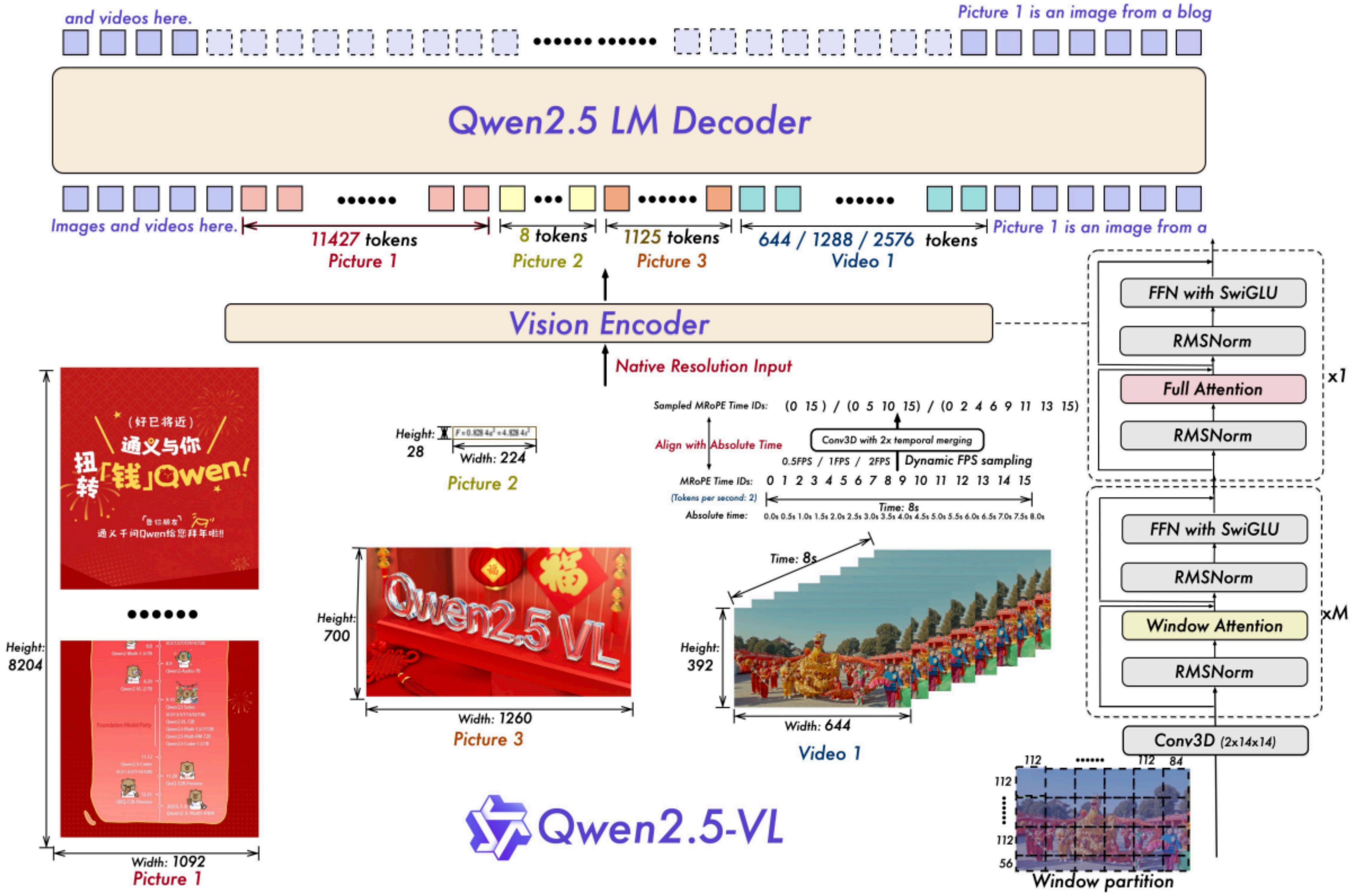
Qwen2.5-VL Technical Report

Qwen Team, Alibaba Group

https://chat.qwenlm.ai
https://huggingface.co/Qwen
https://modelscope.cn/organization/qwen
https://github.com/QwenLM/Qwen2.5-VL



From Show and Tell to Modern Multimodal LLMs

	Show and Tell (2015)	**Qwen2.5-VL (2025)**
Team	Size of 4 (Research Oriented)	Qwen team (Engineering Heavy)
Image encoder	GoogLeNet (~7M)	ViT with native any-res
Language decoder	LSTM (~13M)	LLM
Parameter size	~20M	72B (~4000 times larger)
Model training	GoogLeNet frozen, LSTM from scratch	Pre-training + Post-training
Training data	ImageNet + COCO	Large volume of data
Capabilities	Short image captions + simple VQA etc.	Knowledge-intensive, text-rich, refer & ground, UI, video, reasoning

Advancing MLLMs: Taking Apple Multimodal Research as Example

Seeing

From CLIP to CLOC

From AIM to AIMv2

Understanding

MM1, MM1.5
MM-Ego, MM-Spatial

Ferret, Ferret 2
Ferret-UI, Ferret-UI 2

SlowFast-LLaVA
SlowFast-LLaVA-1.5

Acting

Generalist Embodied Agents

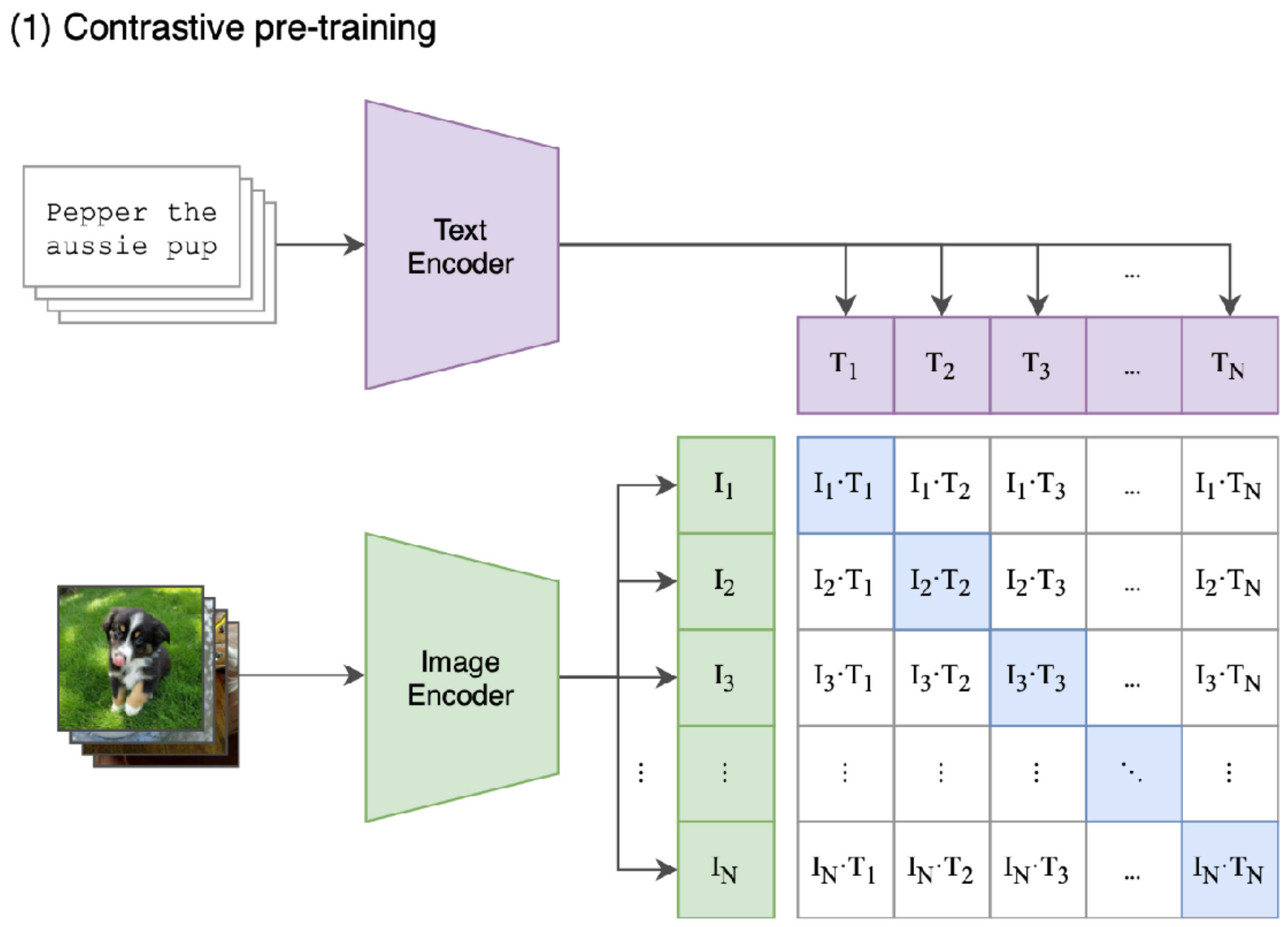
And more to come…

[1] MM-Ego: Towards Building Egocentric Multimodal LLMs, ICLR 2025
[2] MM-Spatial: Exploring 3D Spatial Understanding in Multimodal LLMs, 2025
[3] MOFI: Learning Image Representations from Noisy Entity Annotated Images, ICLR 2024
[4] From Multimodal LLMs to Generalist Embodied Agents: Methods and Lessons, CVPR 2025

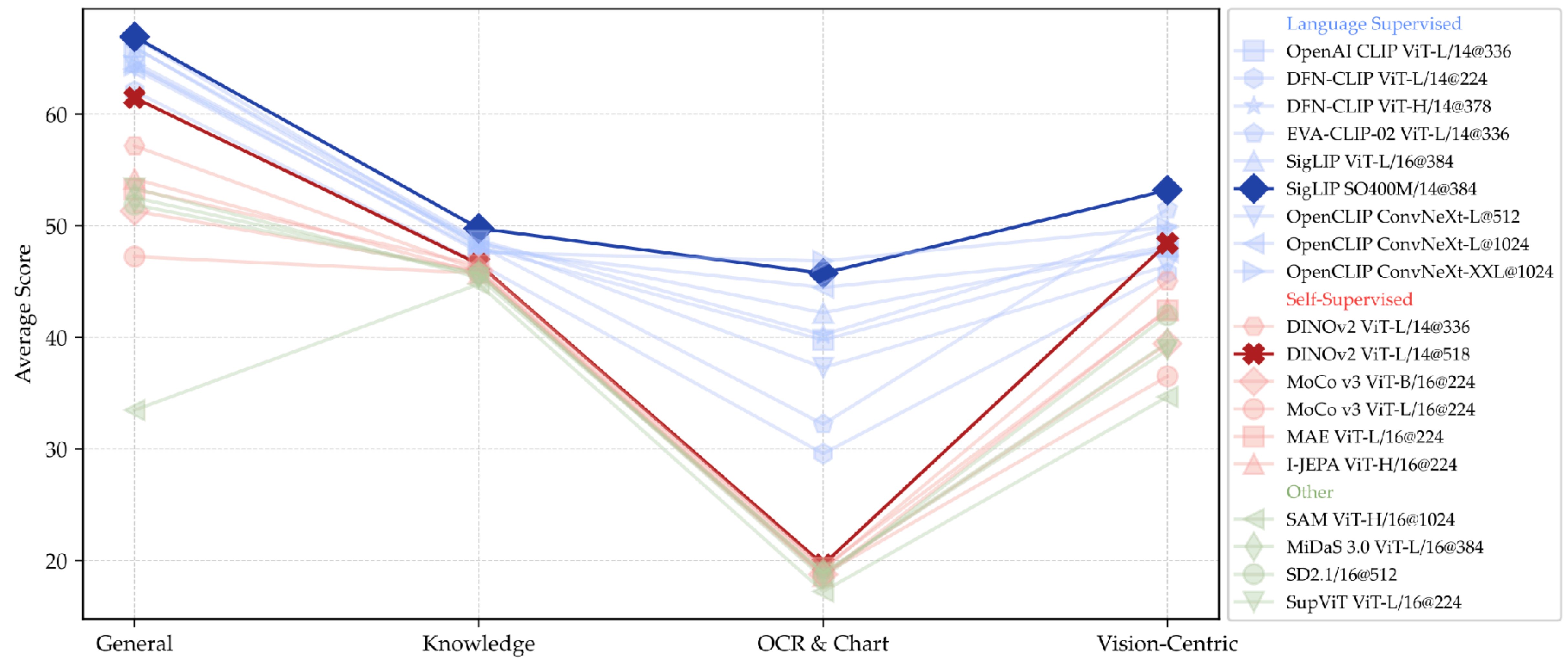
Seeing: From CLIP to CLOC

Can We Do Better than CLIP?

- CLIP has simple design thus appealing scaling properties
- Can we have better image encoder backbones for multimodal LLMs?
- A drop-in replacement for CLIP but with improved localization capability

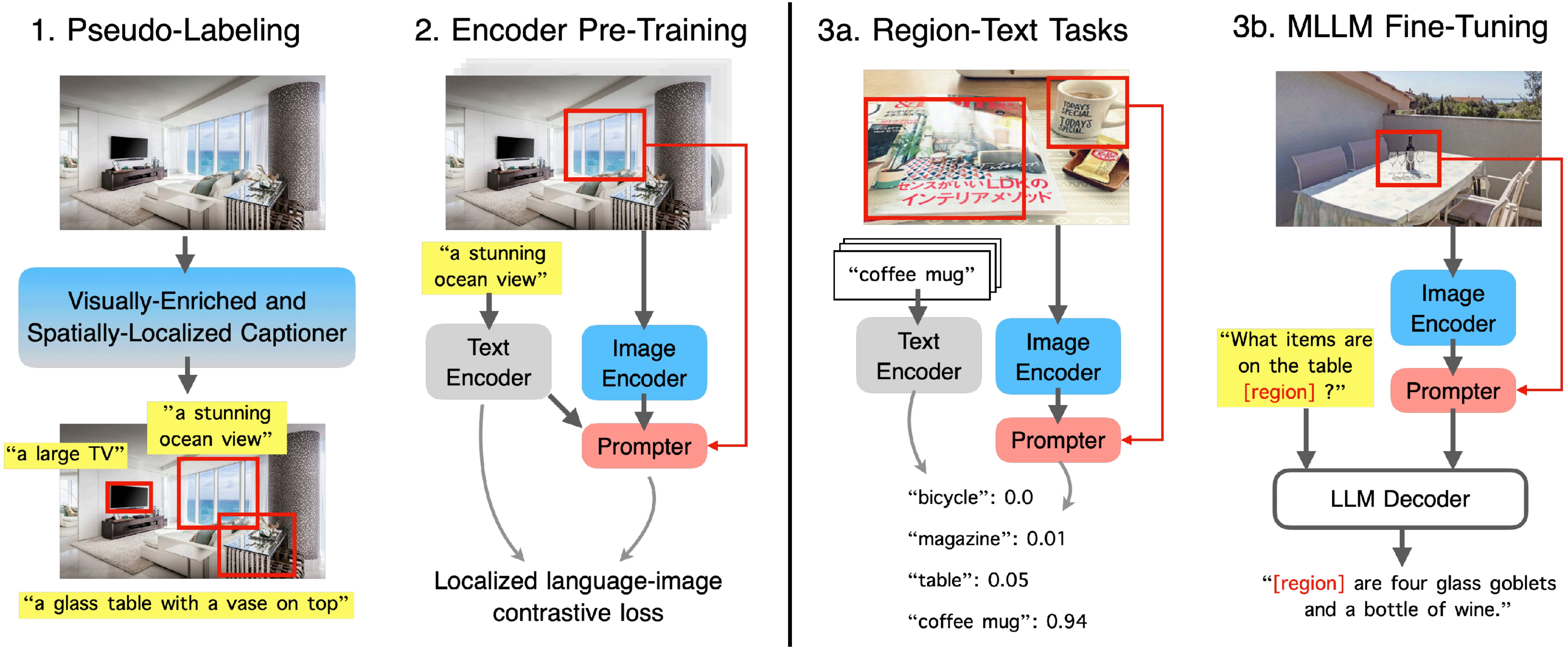


CLIP [Radford et al. 2021]



Cambrian-1 [Tong et al. 2024]

CLOC: Contrastive Localized Language-Image Pre-training



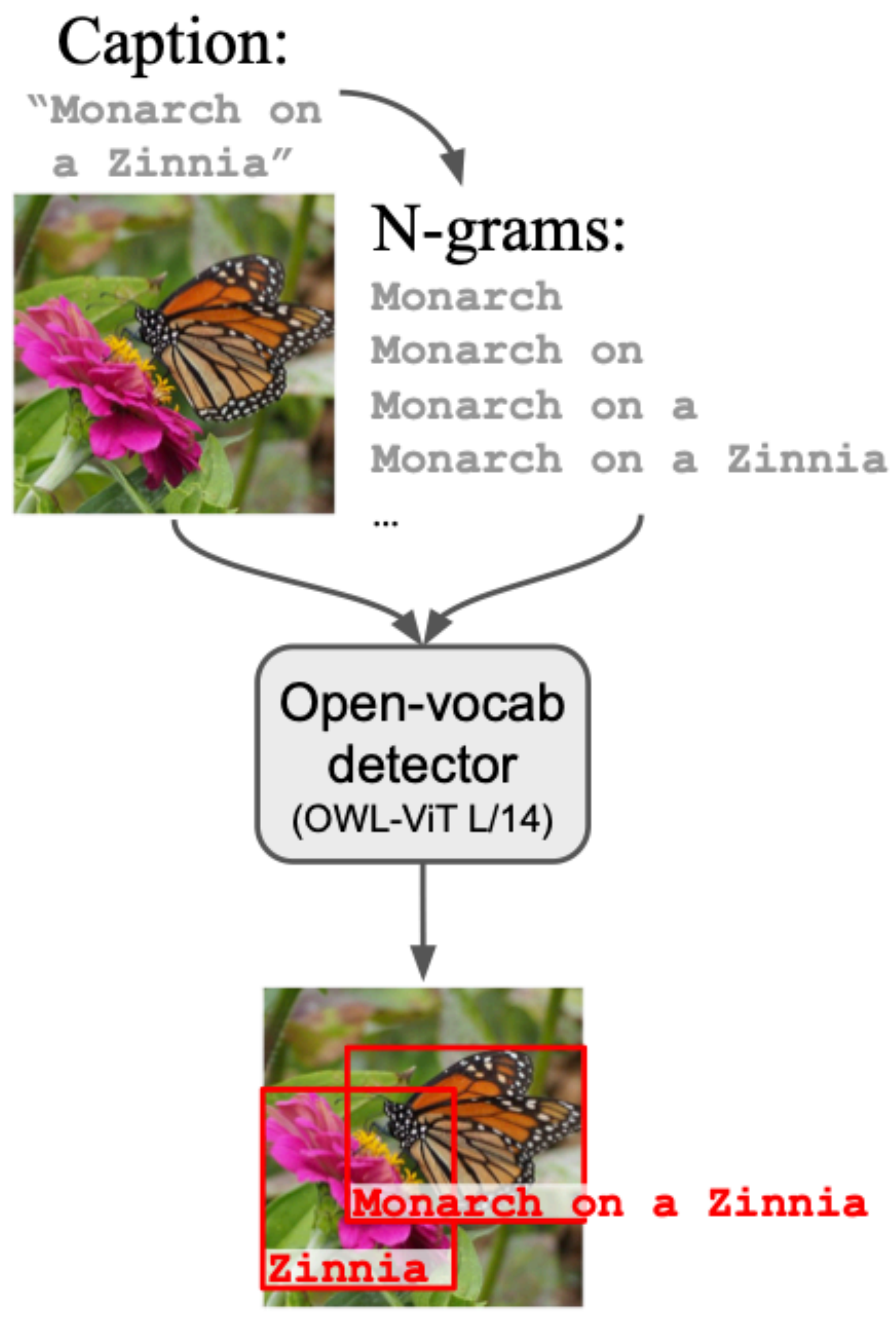
Data: Visually Enriched and Spatially Localized Captioning

Data: Visually Enriched and Spatially Localized Captioning

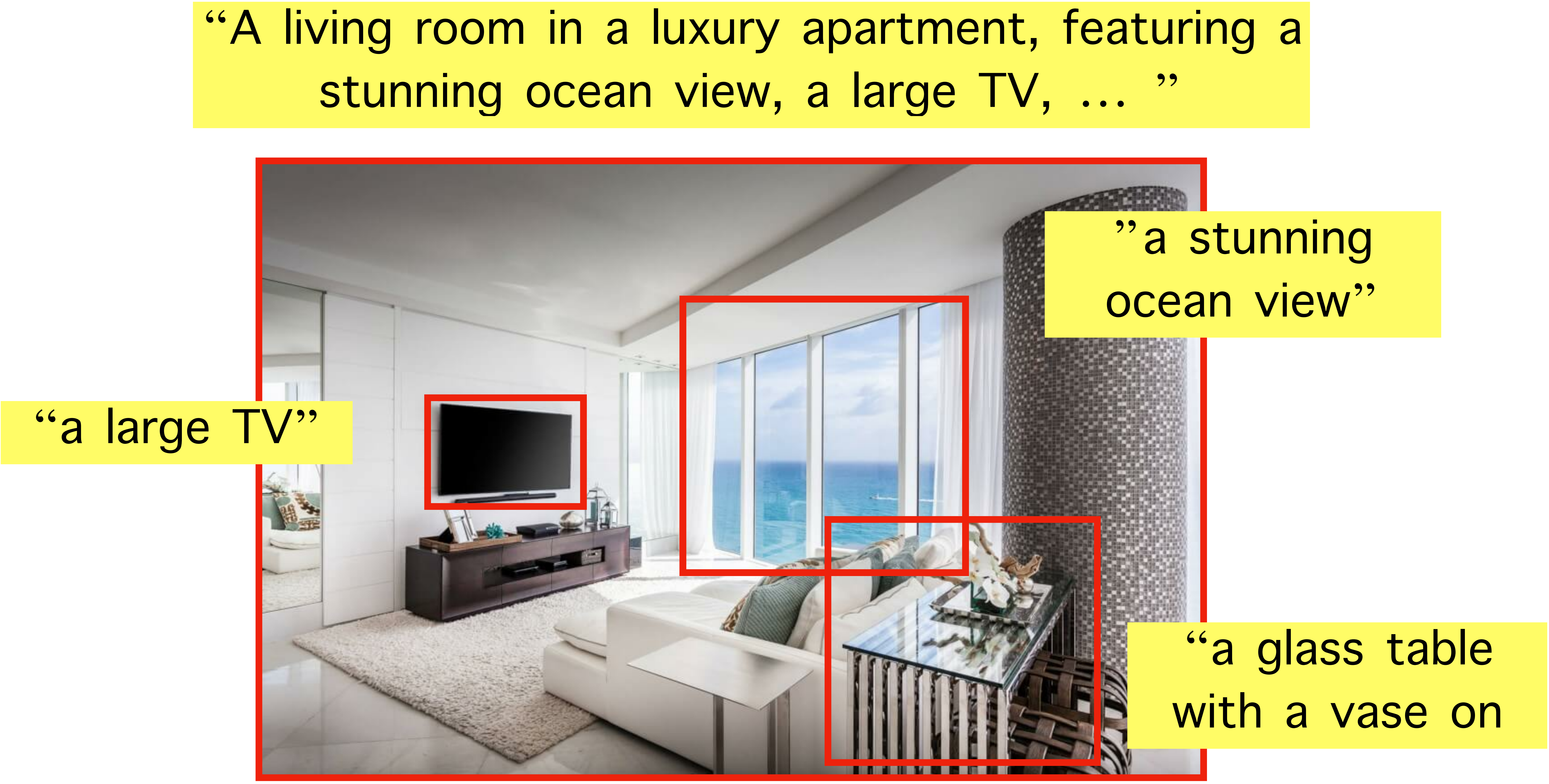
- 2B images with 20B image regions for model training

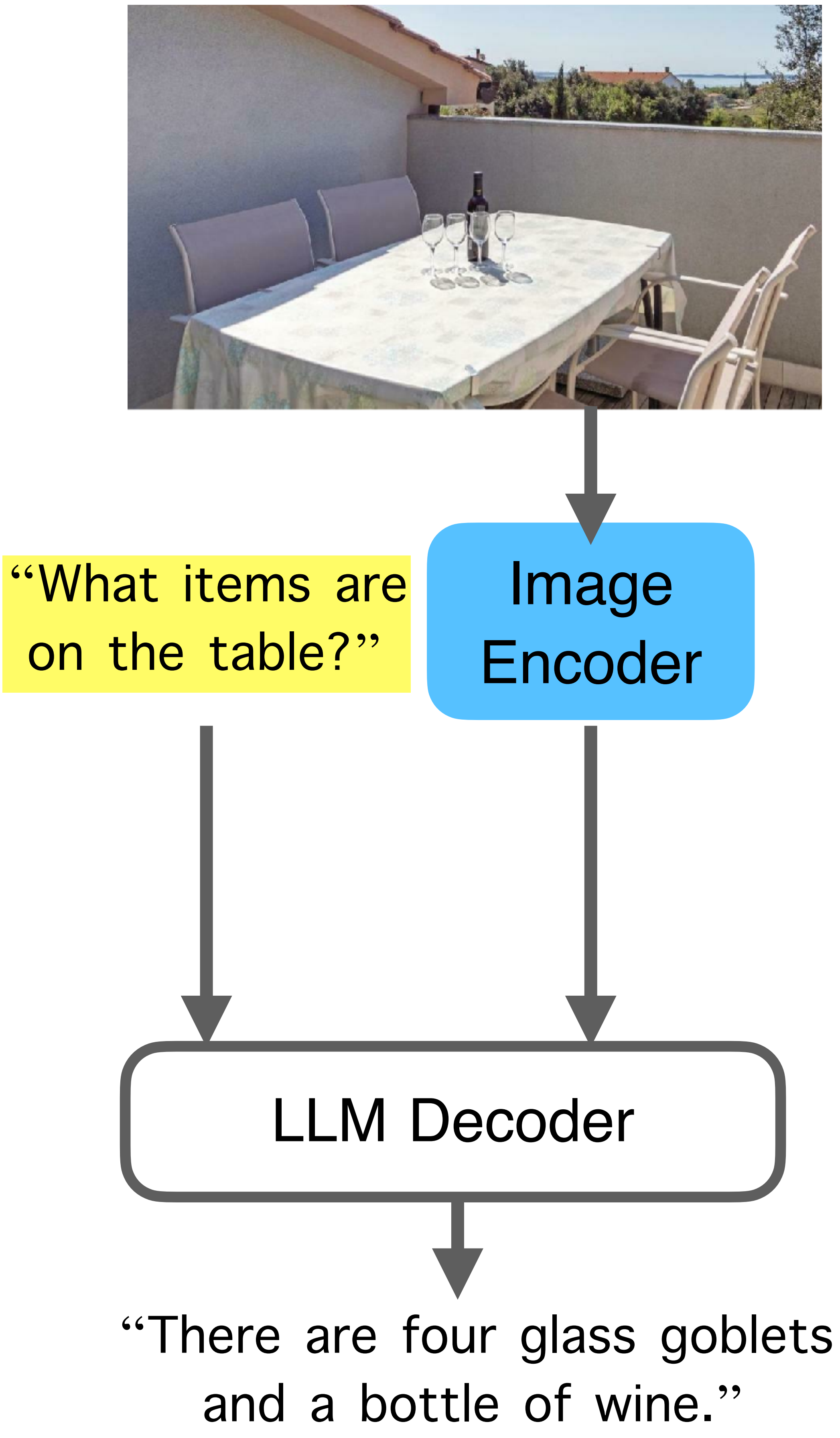
Table 1: **Region-text dataset statistics.** We summarize the text token length for both images and regions. Partial statistics of the proprietary datasets revealed by their papers. *The 20M subset of GRIT is released at: `https://huggingface.co/datasets/zzliang/GRIT`; we removed the invalid images.

Dataset	# of images	regions per image	image caption length	region text length
Flickr Entities (Plummer et al., 2015)	32K	8.7	–	–
RefCOCO (Yu et al., 2016)	20K	2.5	–	3.6
RefCOCO+ (Yu et al., 2016)	20K	2.5	–	3.5
RefCOCOg (Mao et al., 2016)	27K	2.1	–	8.4
Visual Genome (Krishna et al., 2017)	108K	38.0	–	–
GRIT (proprietary) (Peng et al., 2023)	91M	1.5	–	4.7
GRIT (released, clean) (Peng et al., 2023)*	17M	1.8	17.2	4.6
Florence-2 (proprietary) (Xiao et al., 2024)	126M	5.4	70.5	2.6
OWLv2 (proprietary) (Minderer et al., 2024)	2B	–	–	–
WiT labeled w/ Minderer et al. (2024)	300M	5.1	17.1	3.9
VESL WiT (Ours)	300M	11.6	44.9	2.1
VESL WiT+DFN (Ours)	2B	11.5	35.9	2.1



Promptable Embeddings: How to Obtain Region Embeddings

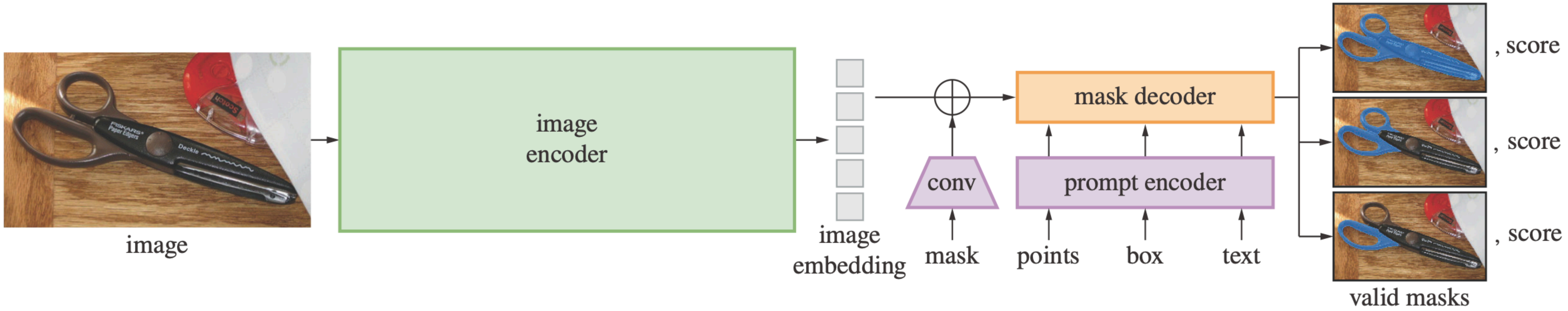




a strong image embedding that can be easily transformed into region representations aligned with fine-grained text, given **visual prompts**

Promotable Embeddings: SAM vs CLOC

- SAM: a prompt —> a mask
- CLOC: a prompt —> a region embedding

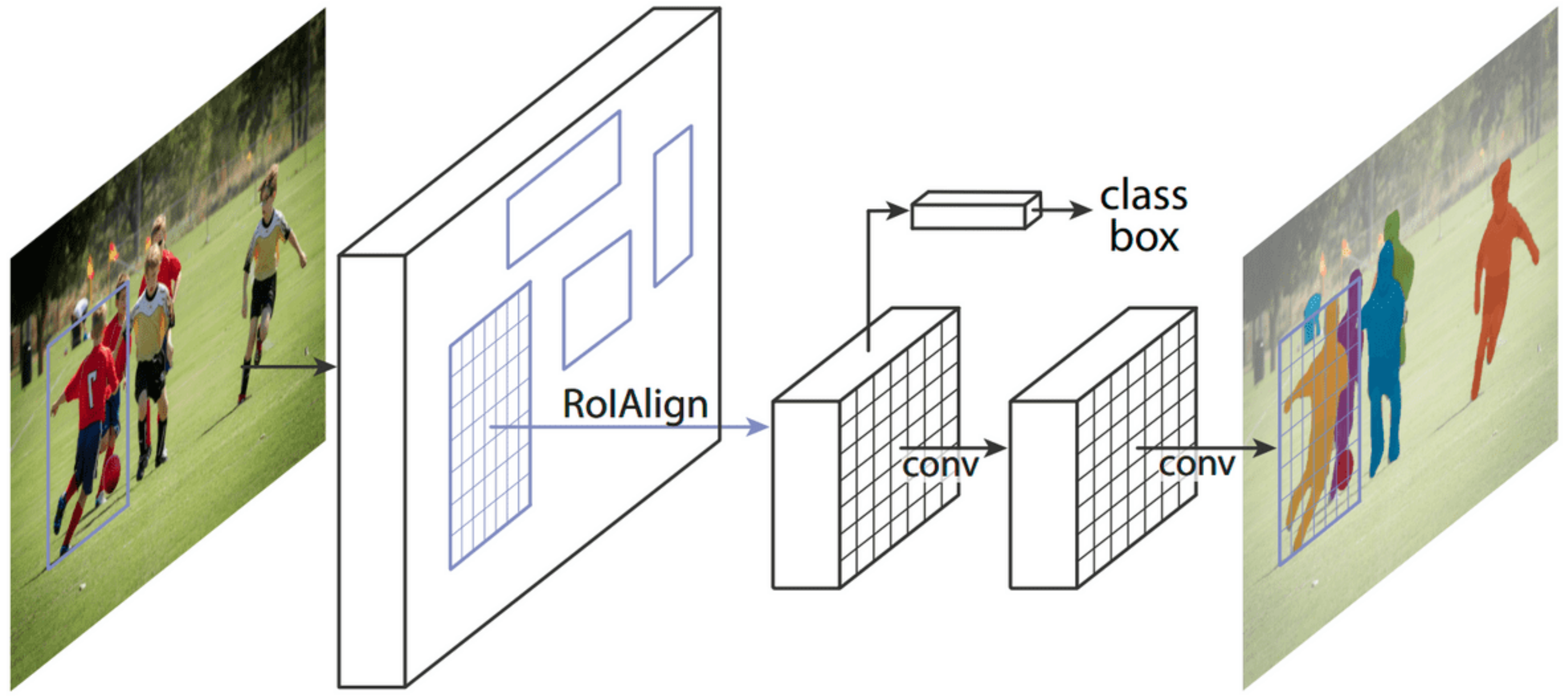


SAM [Kirillov et al. 2023]

Extracting Region Features with a Prompter

- How about RoI-Align?

- Image -> ViT -> spatial feature map -> RoI-Align(box) -> region features



- ViT vs. CNN

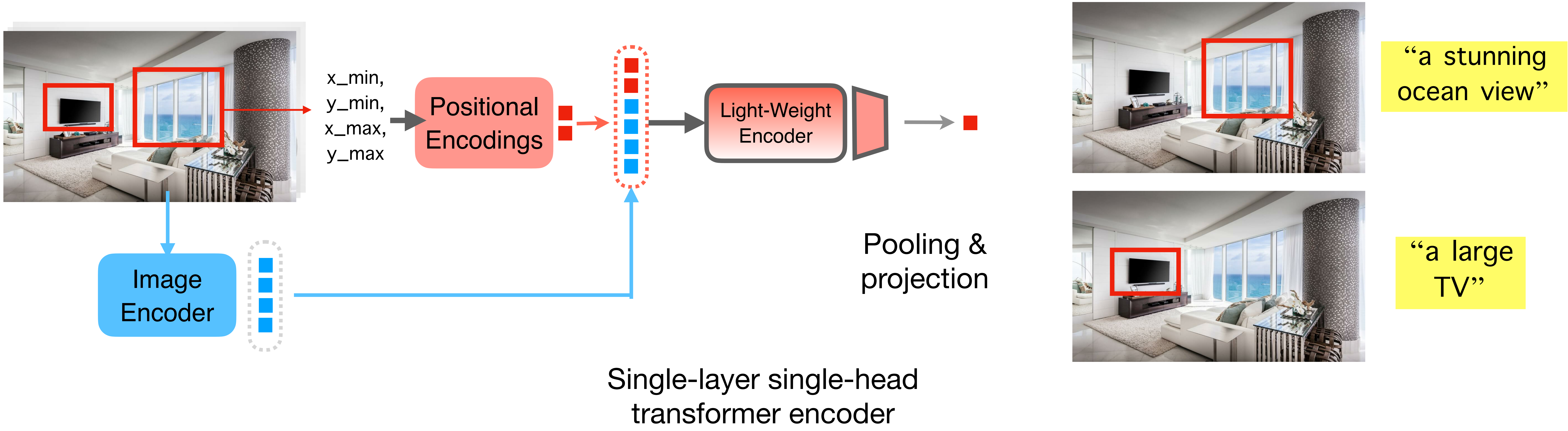
- Inductive bias for downstream MLLM

- Noisy bounding boxes

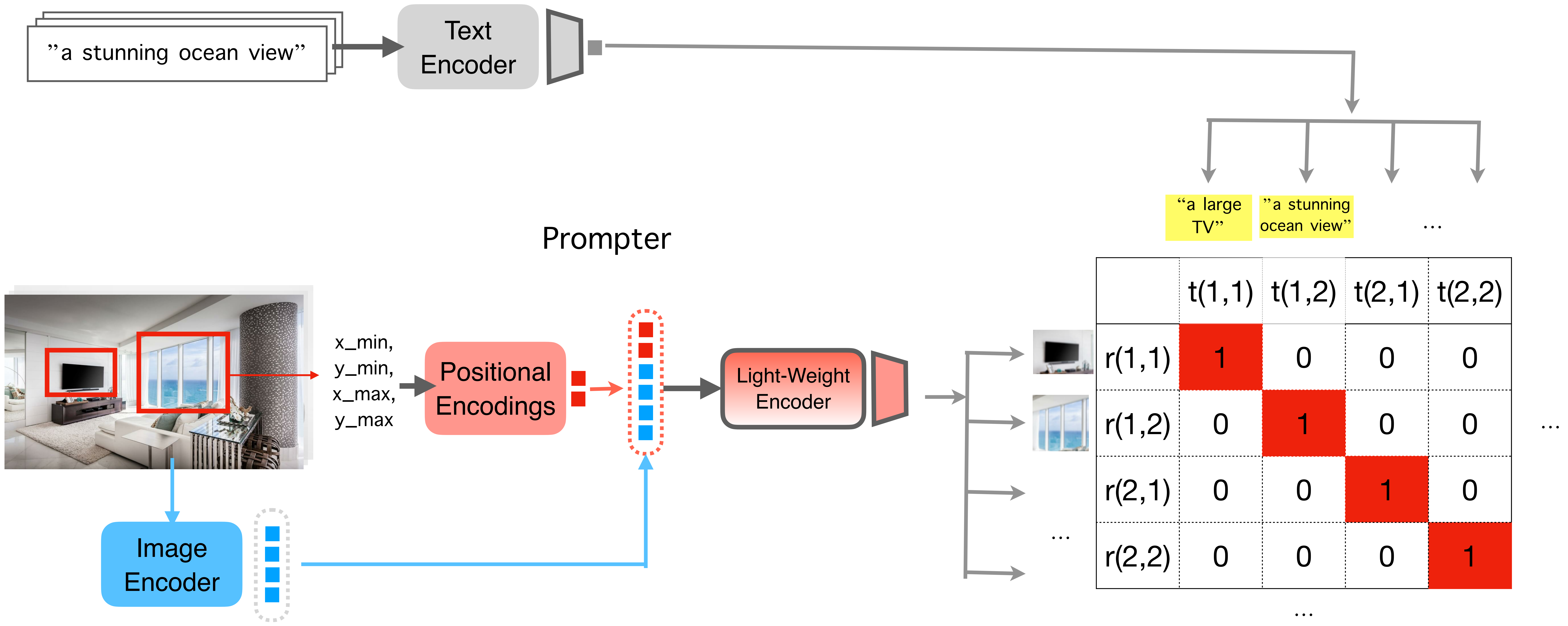
A Simple and Scalable Design for the Prompter

RegionFeature(x, box) =

Prompter (ImageEncoder(x), box)



CLOC: A Localized CLIP Training Loss

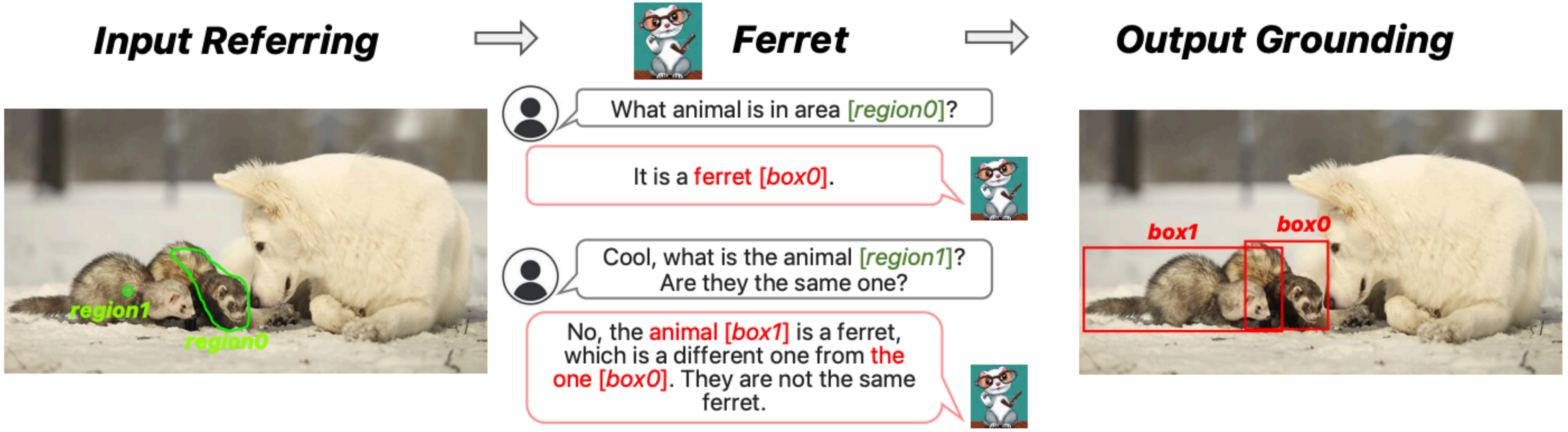


RegionFeature(x, box) = Prompter (ImageEncoder(x), box)

$\mathcal{L}_{\text{CLOC}}$

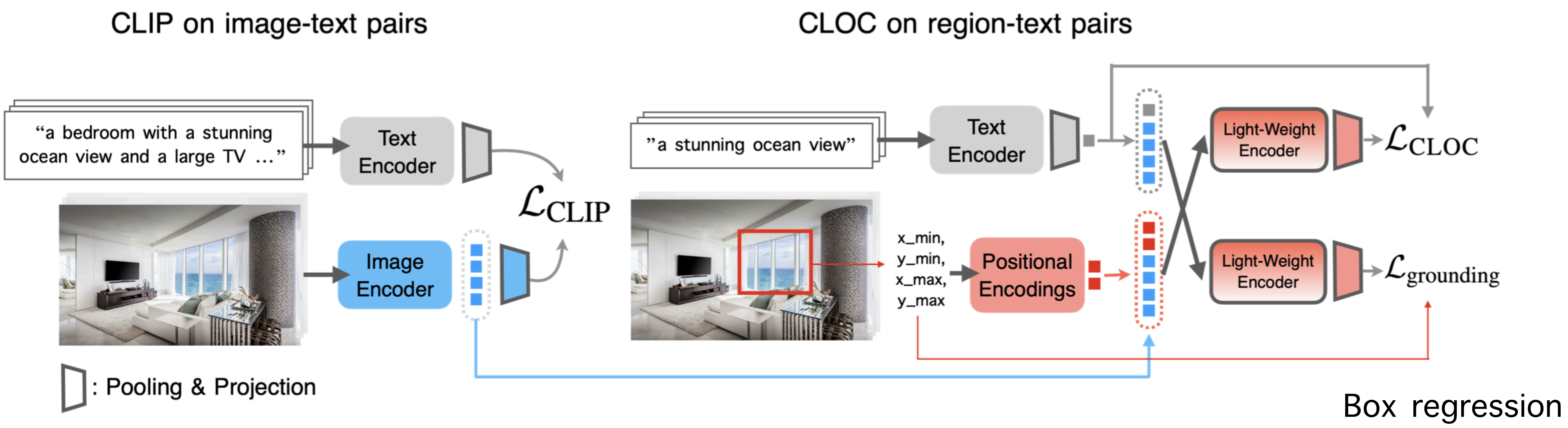
Referring and Grounding in Ferret

- Mimic the concept of referring and grounding for model training
  - Referring: visual prompt —> text output
  - Grounding: text input —> grounded bbox output

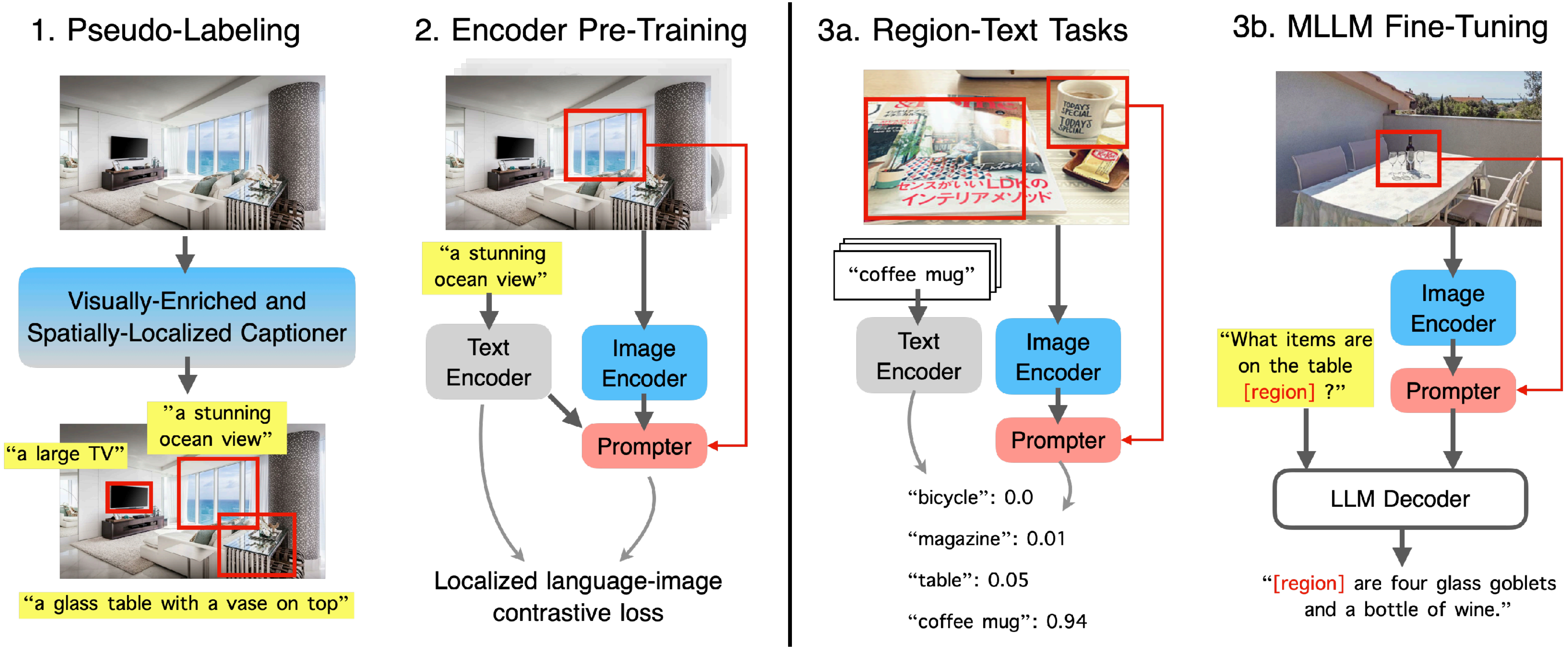


Overall CLOC training

- Referring: bbox —> region caption (i.e., the CLOC loss)
- Grounding: region caption —> bbox (i.e., an additional box regression loss)



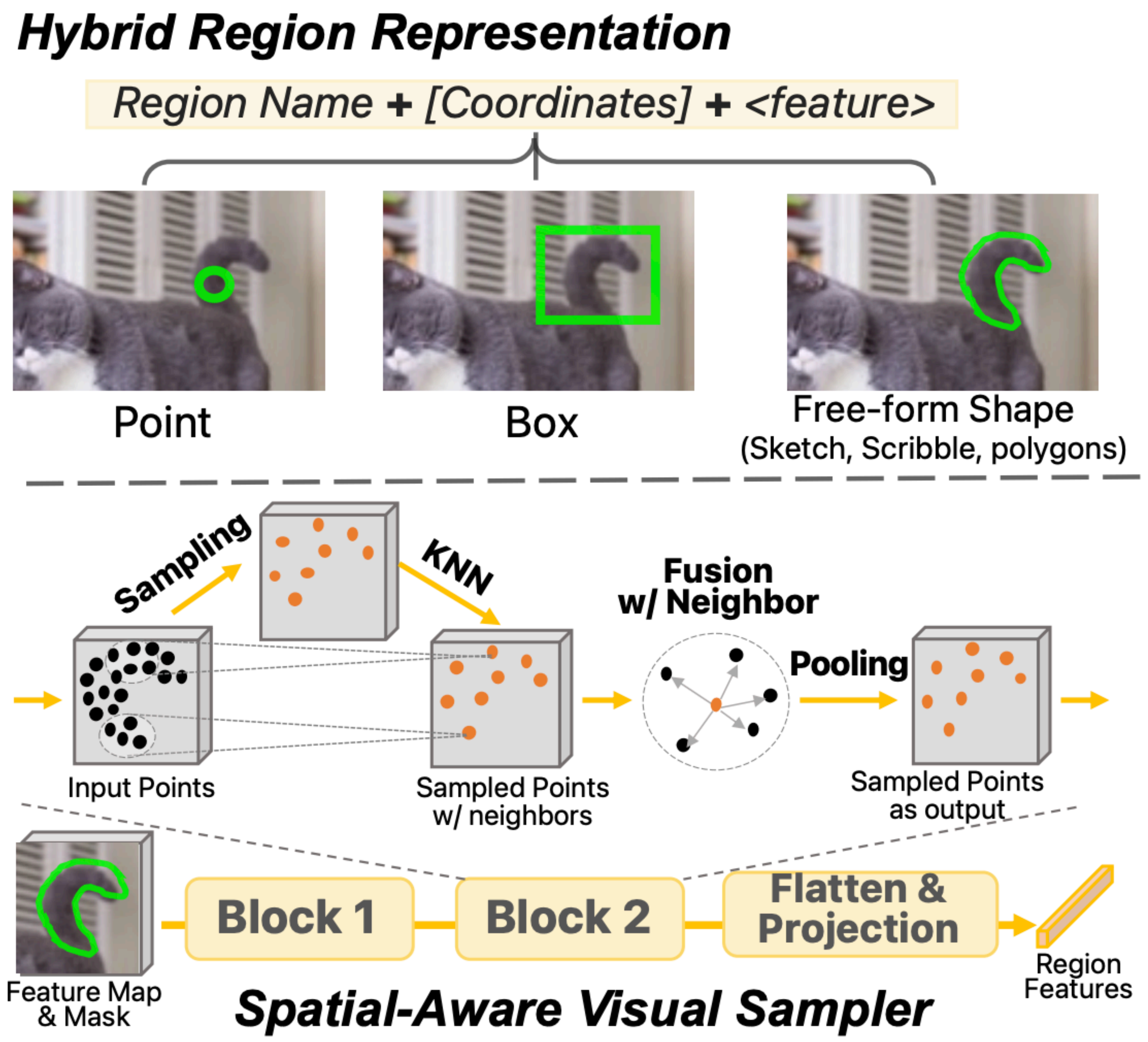
How to Use it for Multimodal LLM?



Translates into Improved Referring and Grounding in MLLM

Method	ViT	Region Alignment	# of images w/ region labels	Referring Description	Referring Reasoning	Grounding in Conversation	Avg. (Δ to CLIP)
CLIP	B/16	None	None	47.5	50.3	45.3	47.7
CLOC	B/16	RoI-Align	300M	48.0	48.4	40.0	45.5
CLOC	B/16	`Prompter`	300M	50.2	55.5	41.5	49.1
CLOC	B/16	`Prompter`	2B	53.6	53.7	42.2	49.8 (+2.1)
CLOC *	B/16	`Prompter`	2B	54.8	54.9	44.7	**51.5** (+3.7)
OpenAI-CLIP	L/14	None	None	50.8	55.4	45.7	50.6
CLIP	L/14	None	None	54.2	54.6	43.3	50.7
CLOC	L/14	`Prompter`	300M	51.0	65.7	44.9	53.9
CLOC	L/14	`Prompter`	2B	55.9	63.3	46.0	55.1 (+4.4)
CLOC *	L/14	`Prompter`	2B	56.3	67.4	47.1	**56.9** (+6.2)

Model	Encoder	LVIS			RefCOCO			RefCOCO+			RefCOCOg		Flickr		Avg.
		box	point	free-form	val	testA	testB	val	testA	testB	val	test	val	test	(Δ to CLIP)
FERRET	CLIP B/16	72.5	56.9	57.2	80.7	84.2	77.1	71.9	76.1	63.7	75.9	76.2	76.2	78.3	72.8
FERRET	CLOC B/16	74.3	56.7	60.2	84.2	87.0	80.0	74.7	80.0	67.0	78.8	79.5	80.0	81.5	75.7 (+2.9)
FERRET *	CLOC B/16	78.9	58.2	61.4	84.4	86.8	78.9	74.0	78.7	65.5	78.0	78.7	80.1	81.4	**75.8** (+3.0)
Shikra	OpenAI-CLIP L/14	57.8	67.7	n/a	87.0	90.6	80.2	81.6	87.4	72.1	82.3	82.2	75.8	76.5	-
FERRET	OpenAI-CLIP L/14	79.4	67.9	69.8	87.5	91.4	82.5	80.8	87.4	73.1	83.9	84.8	80.4	82.2	80.8
FERRET	CLIP L/14	78.7	66.9	70.2	88.0	90.4	83.5	80.1	85.8	73.3	82.8	83.4	79.0	80.1	80.2
FERRET	CLOC L/14	81.6	67.9	69.9	89.0	91.0	84.7	81.4	86.8	74.7	84.0	85.2	82.3	83.3	**81.7** (+1.5)
FERRET *	CLOC L/14	79.8	67.9	69.1	88.2	91.1	84.5	80.6	86.7	73.9	84.8	85.1	82.4	83.5	81.4 (+1.2)

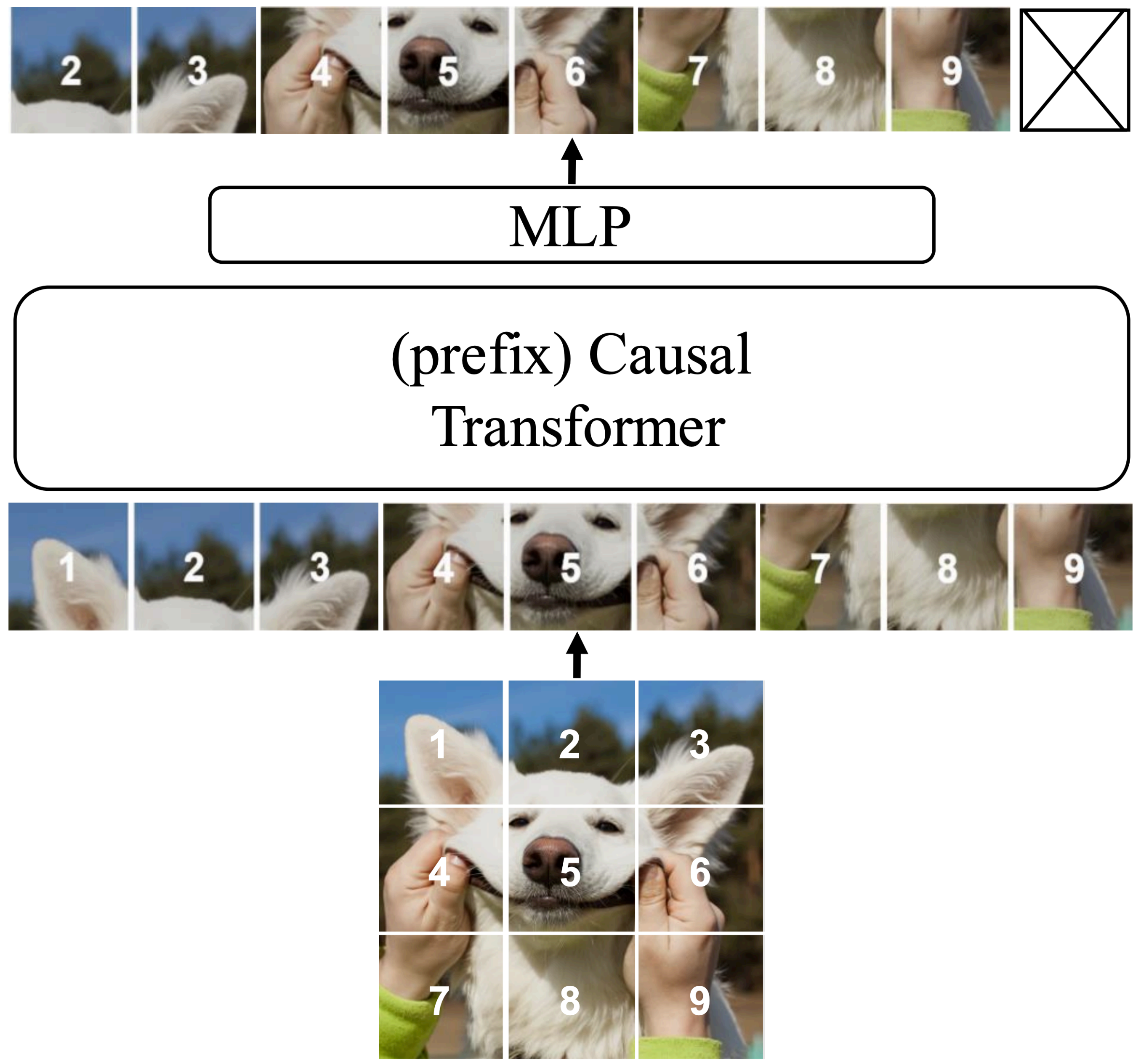


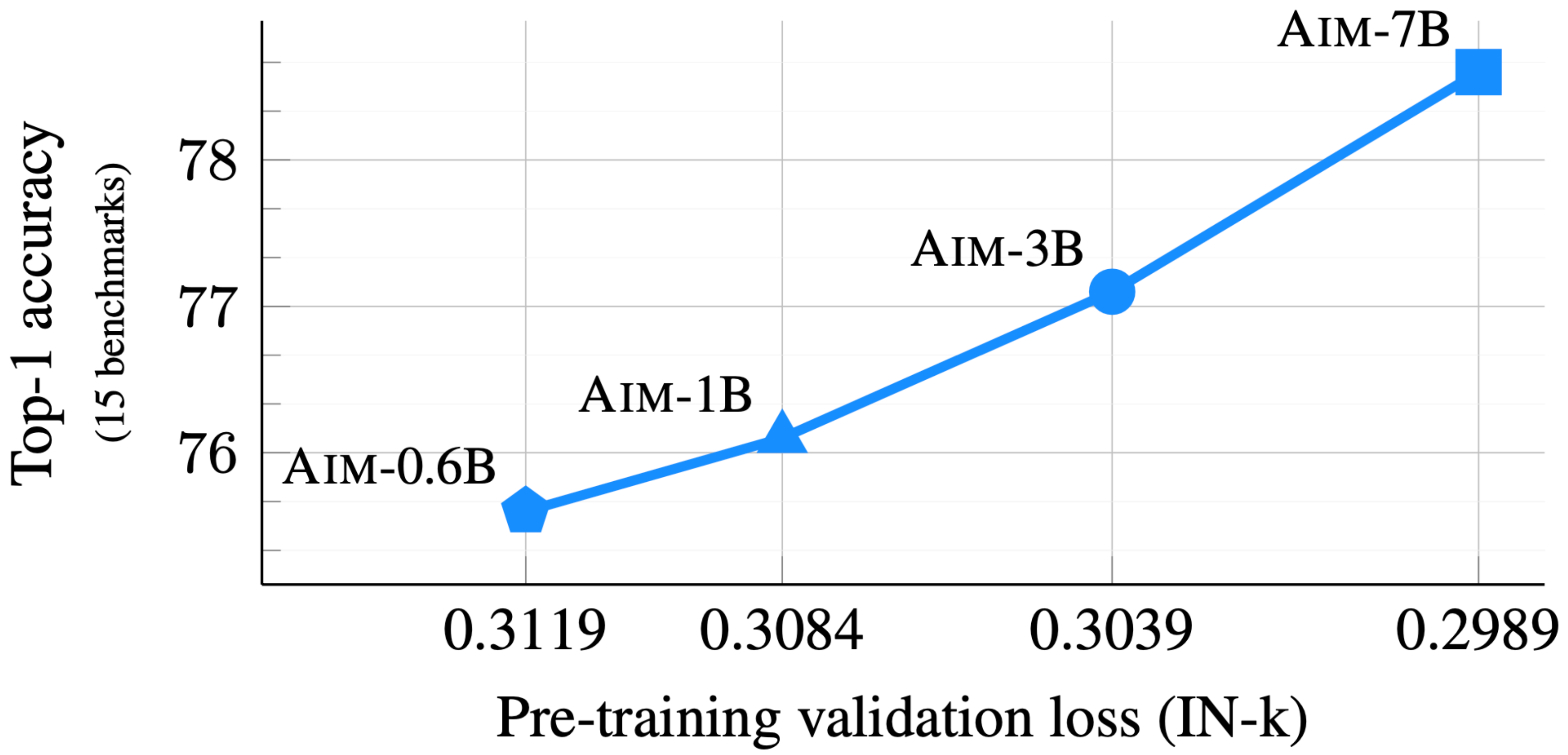
* replace Ferret visual sampler with a simple prompter

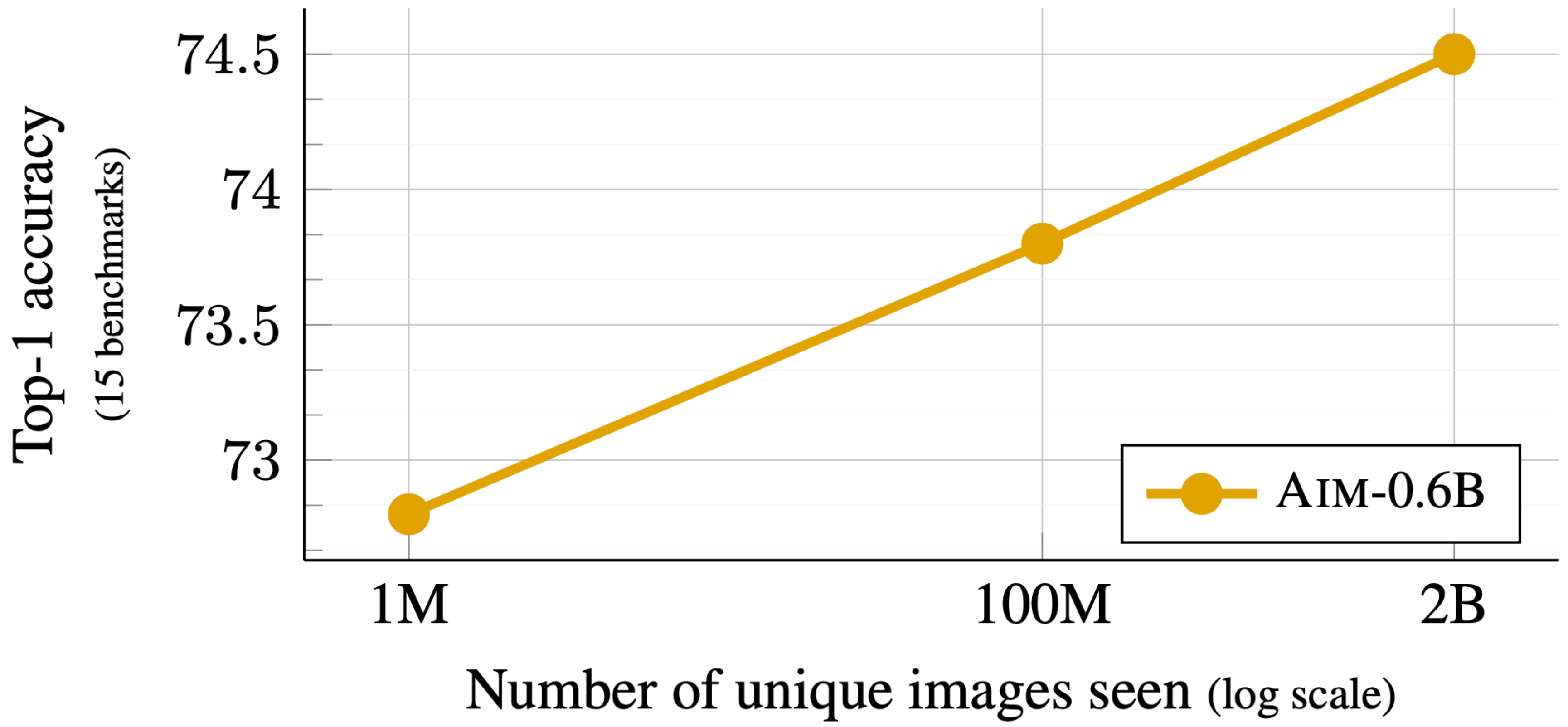
Seeing: From AIM to AIMv2

Autoregressive Image Models (AIM)

- Pre-train an image encoder only using autoregressive image pixel losses

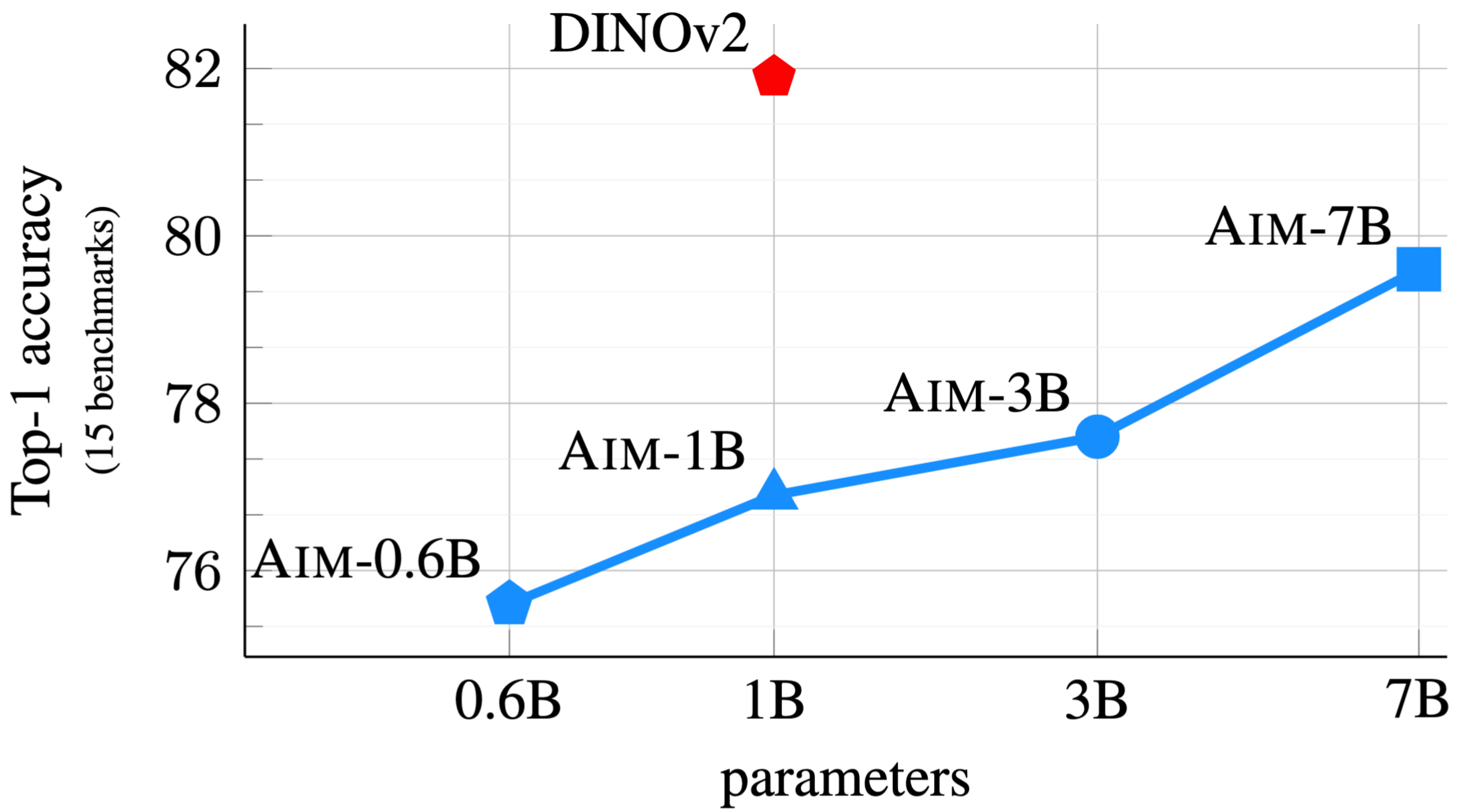






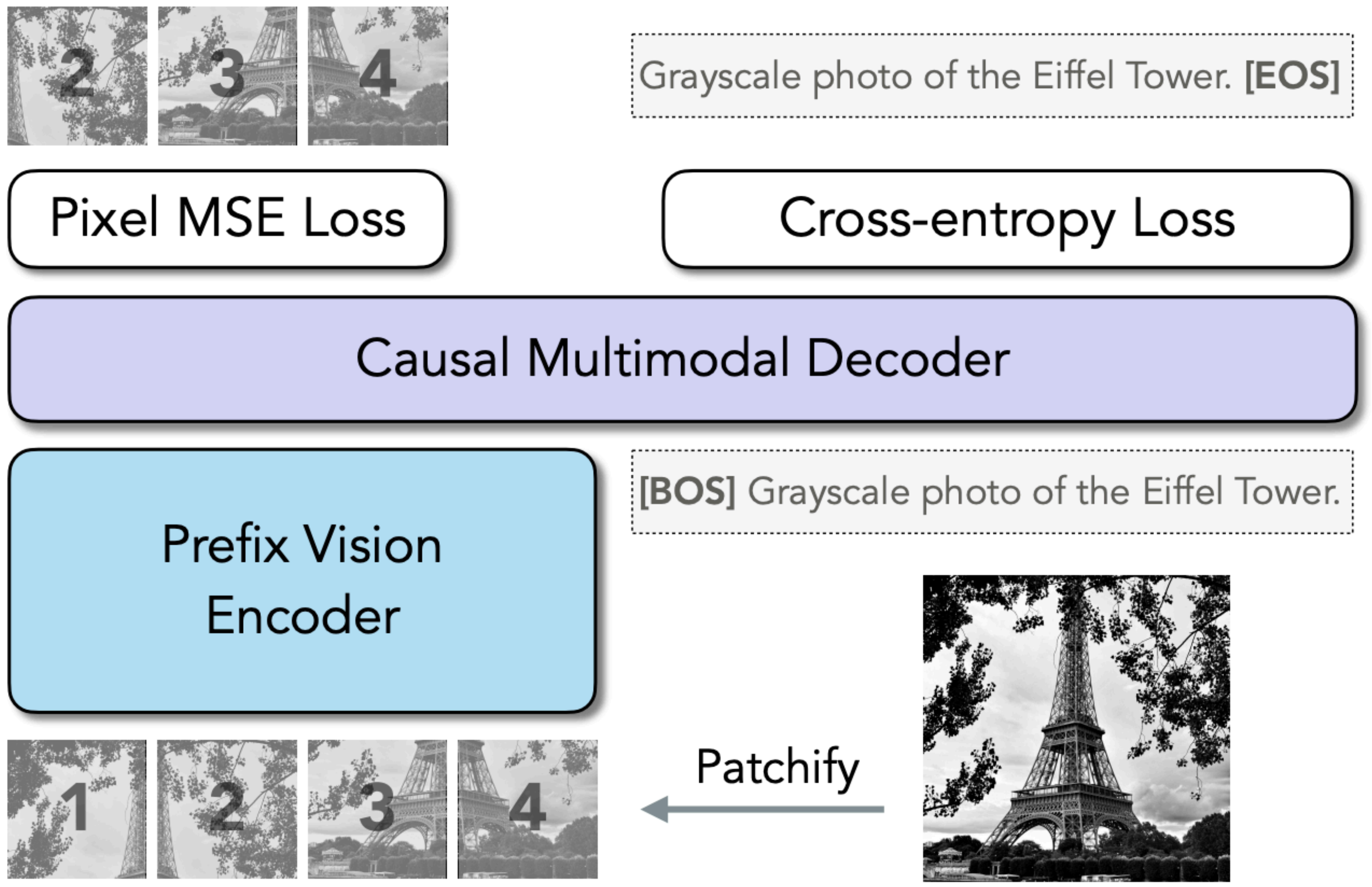
Autoregressive Image Models (AIM)

- Contrastive/Joint embedding (e.g., DINOv2) methods are still more parameter efficient!



Multimodal Autoregressive Pre-training

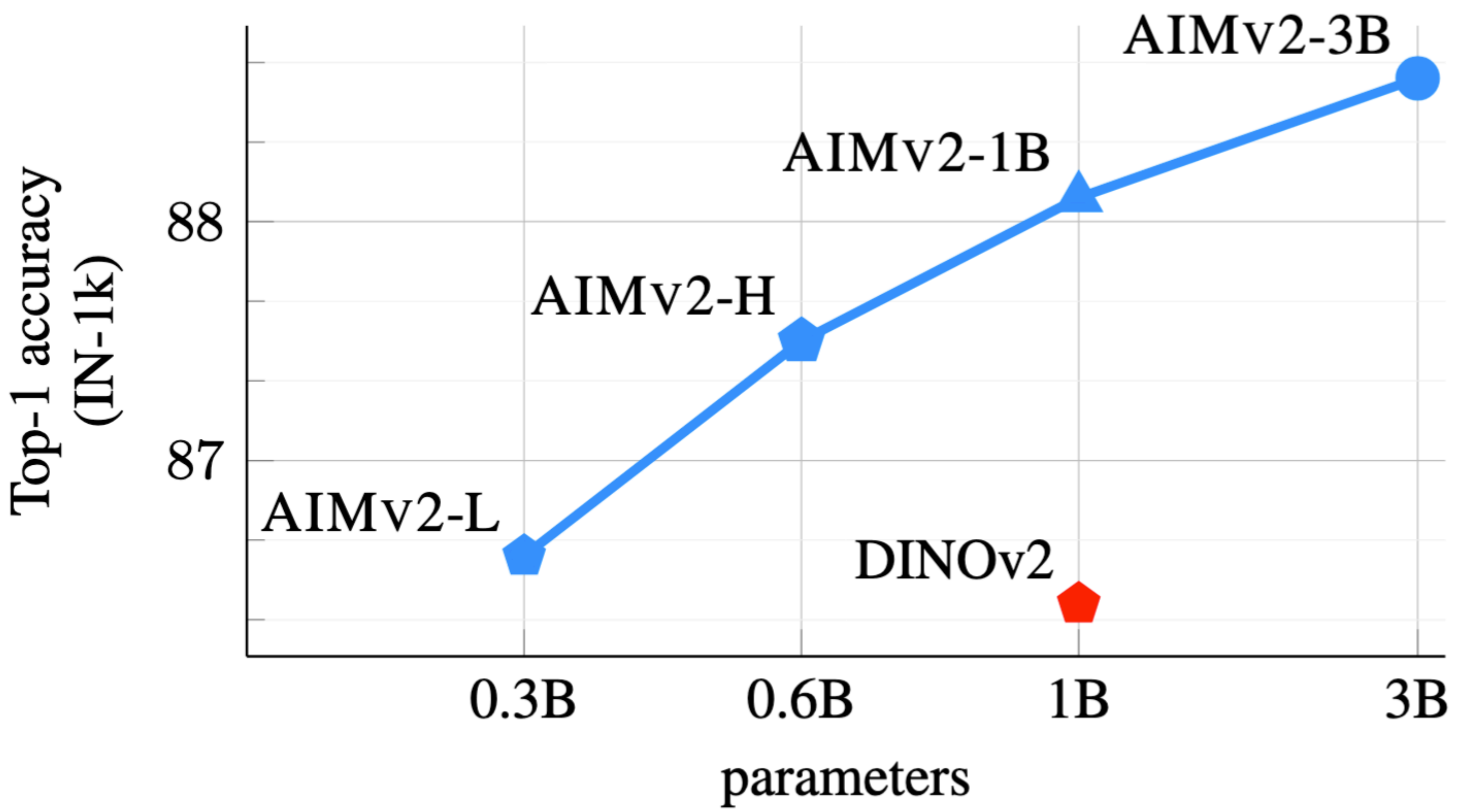
- AIMv2 is a paradigm shift from the predominant CLIP pre-training

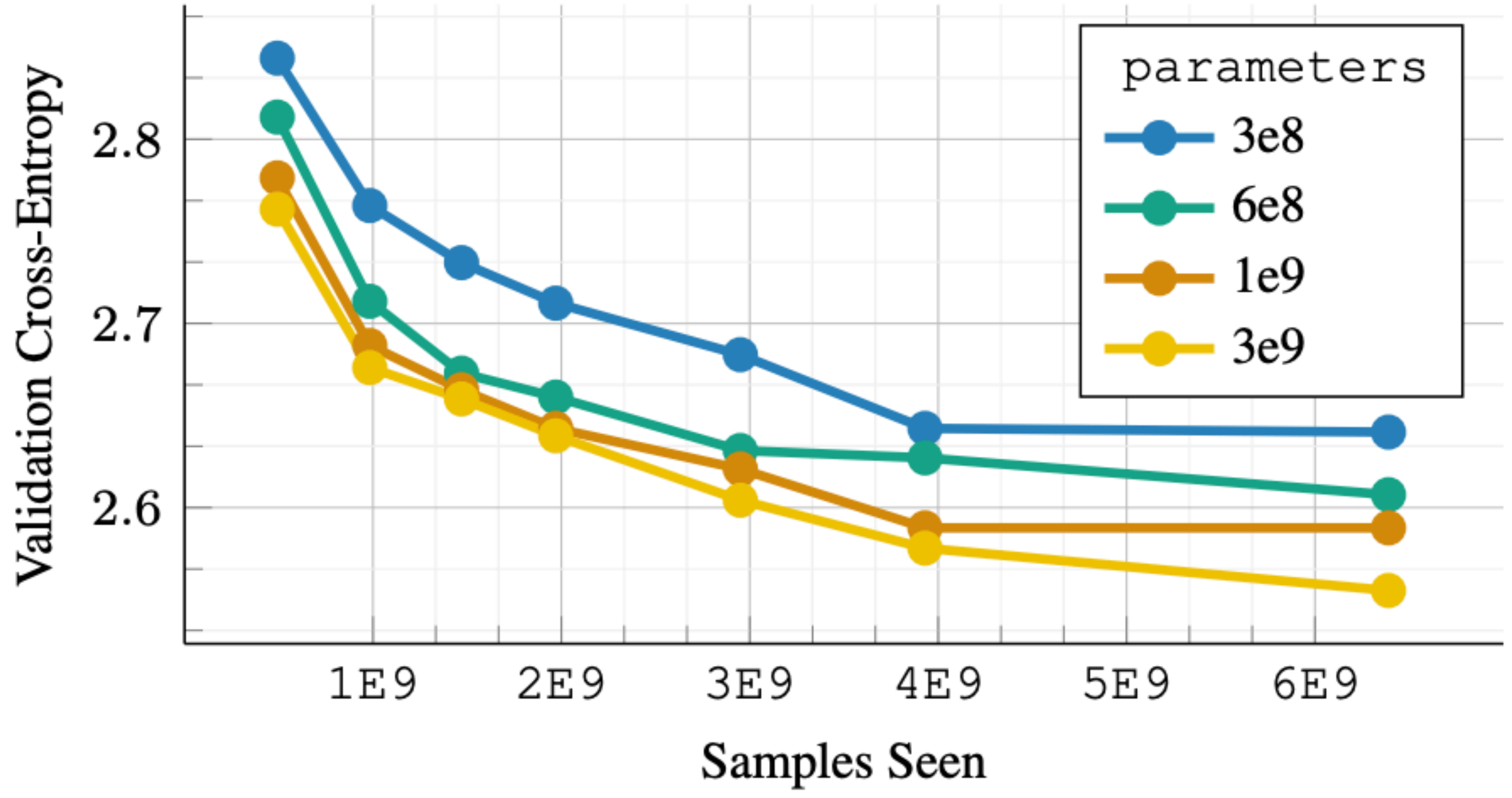


- Purely autoregressive objective, easy to scale and parallelize (e.g., no intra-batch sync required)
- Dense supervision with a loss term per token rather than a single global loss
- Better alignment with the multimodal LLM use cases.

Scaling Properties of AIMv2

- Scaling in terms of model size and data size

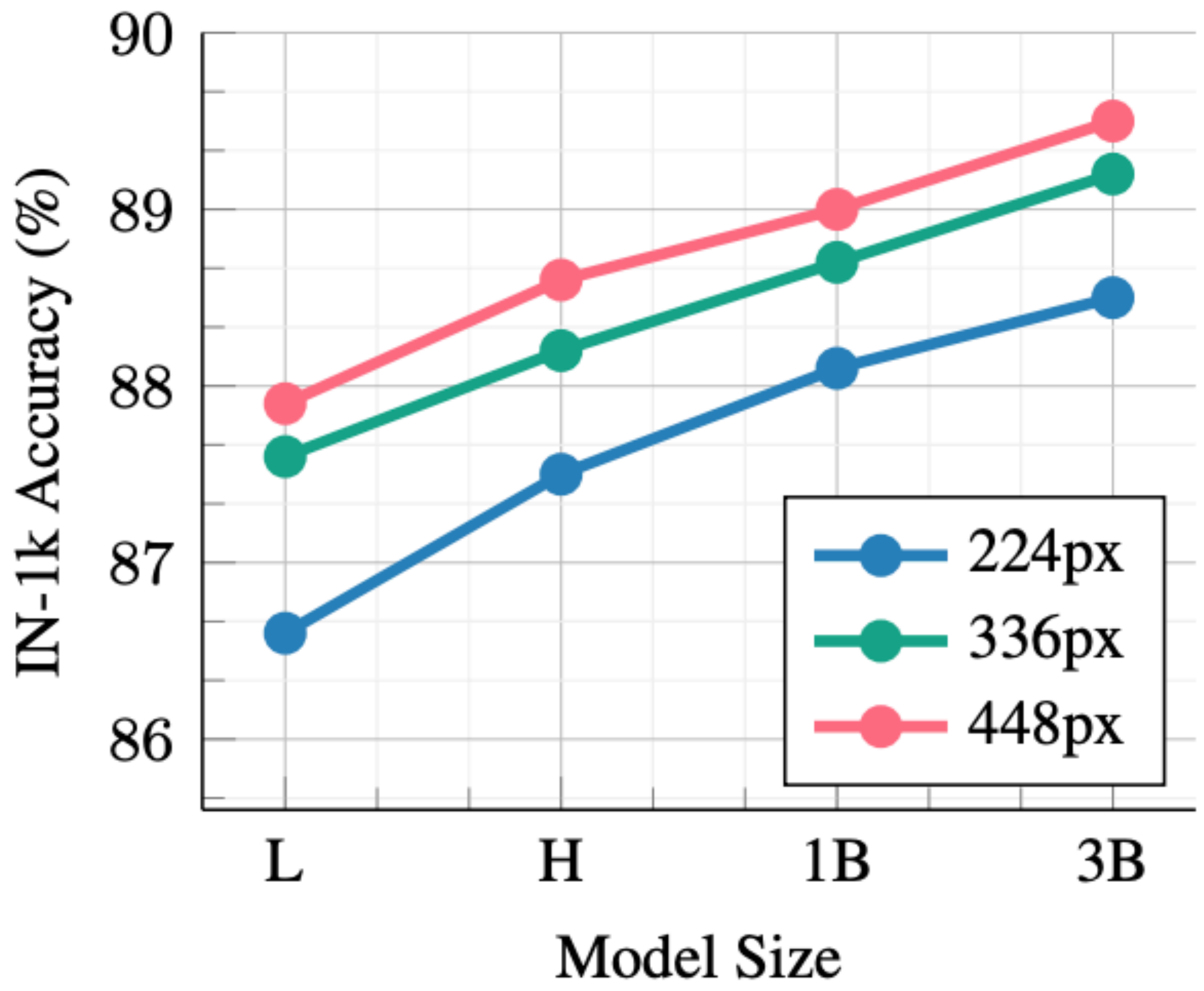




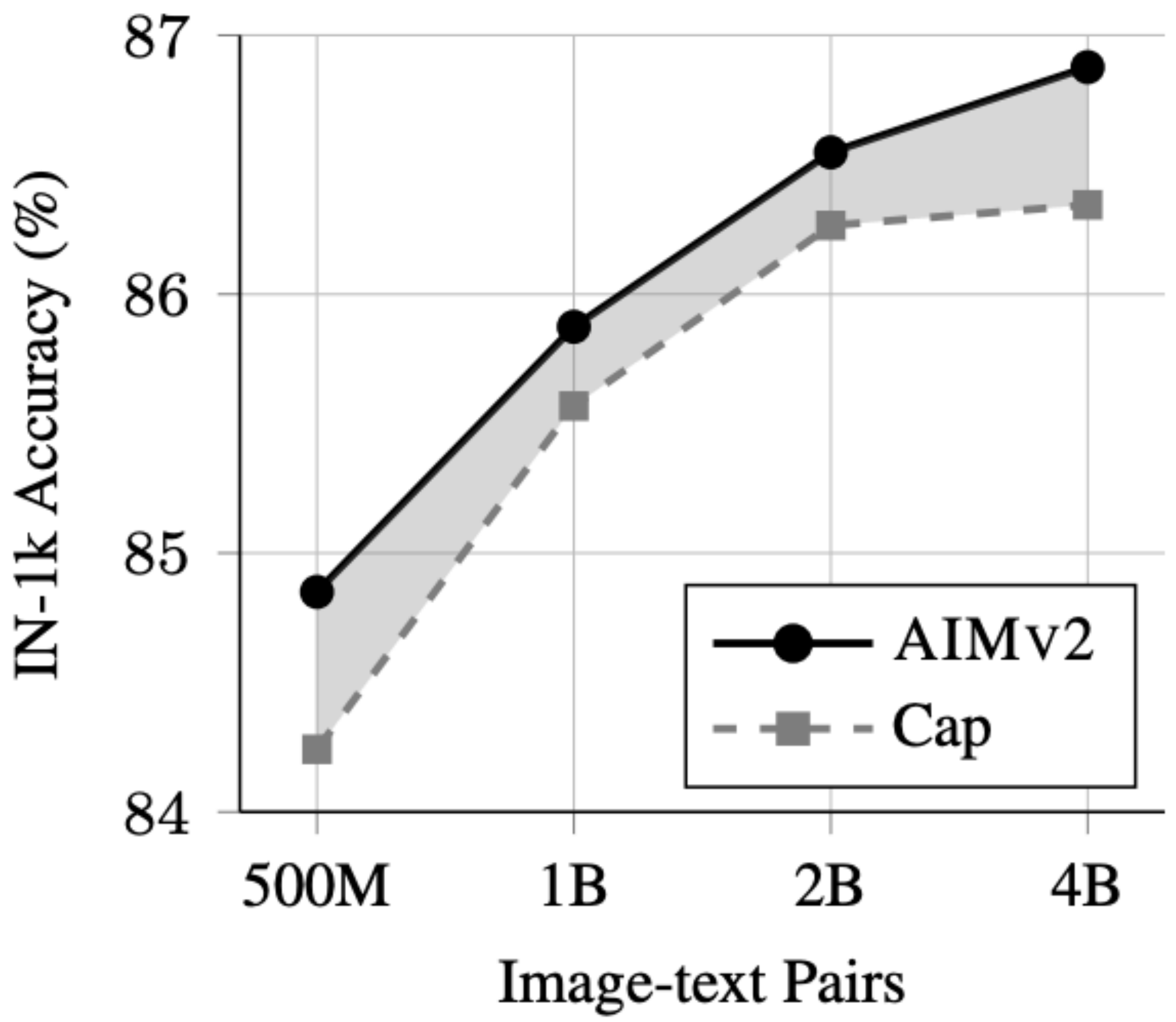
AIMv2 is another example of simple methods that scale well!

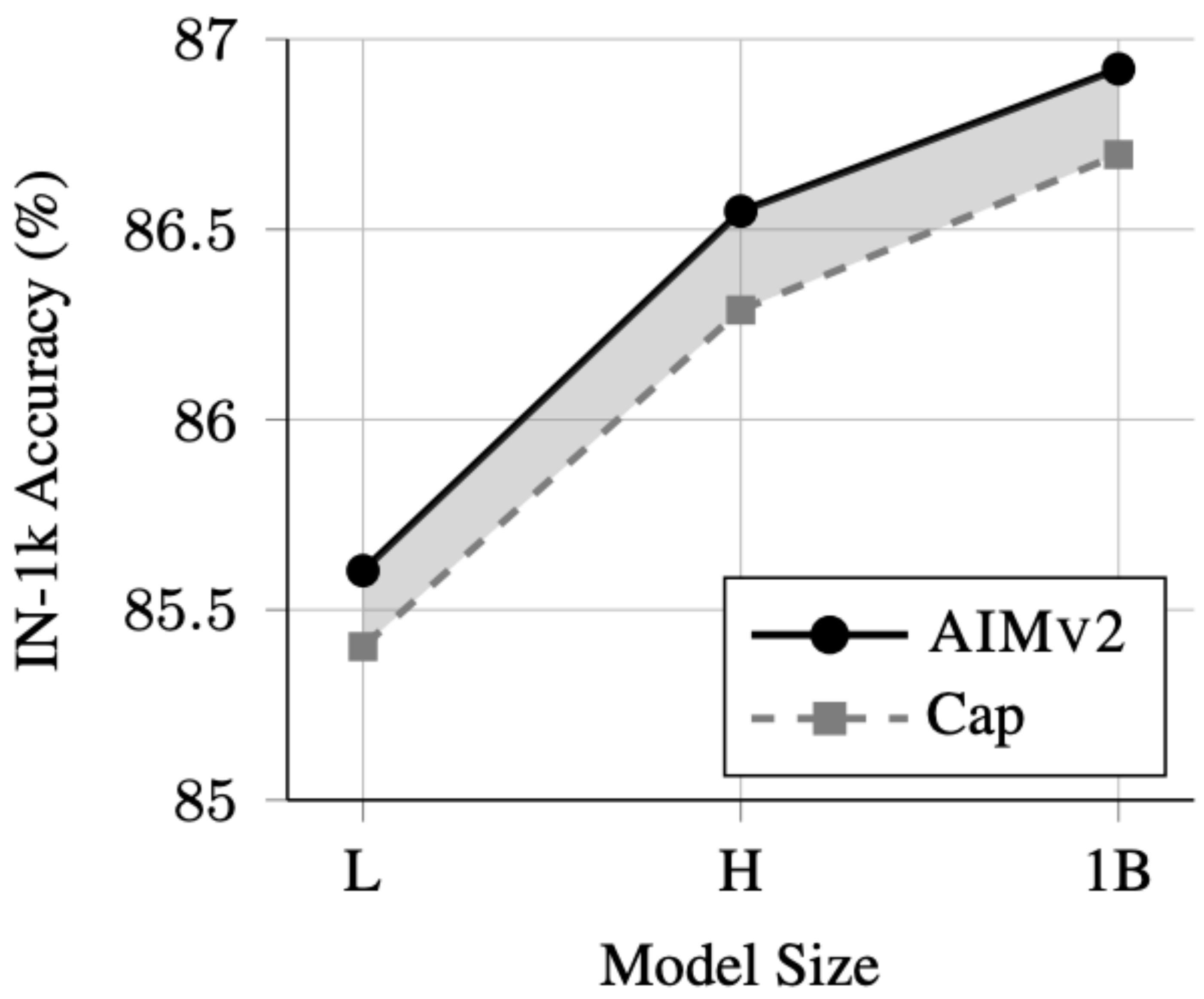
Scaling Properties of AIMv2

Scaling in terms of image resolution



AIMv2 vs Captioning





Other Good Works Out There

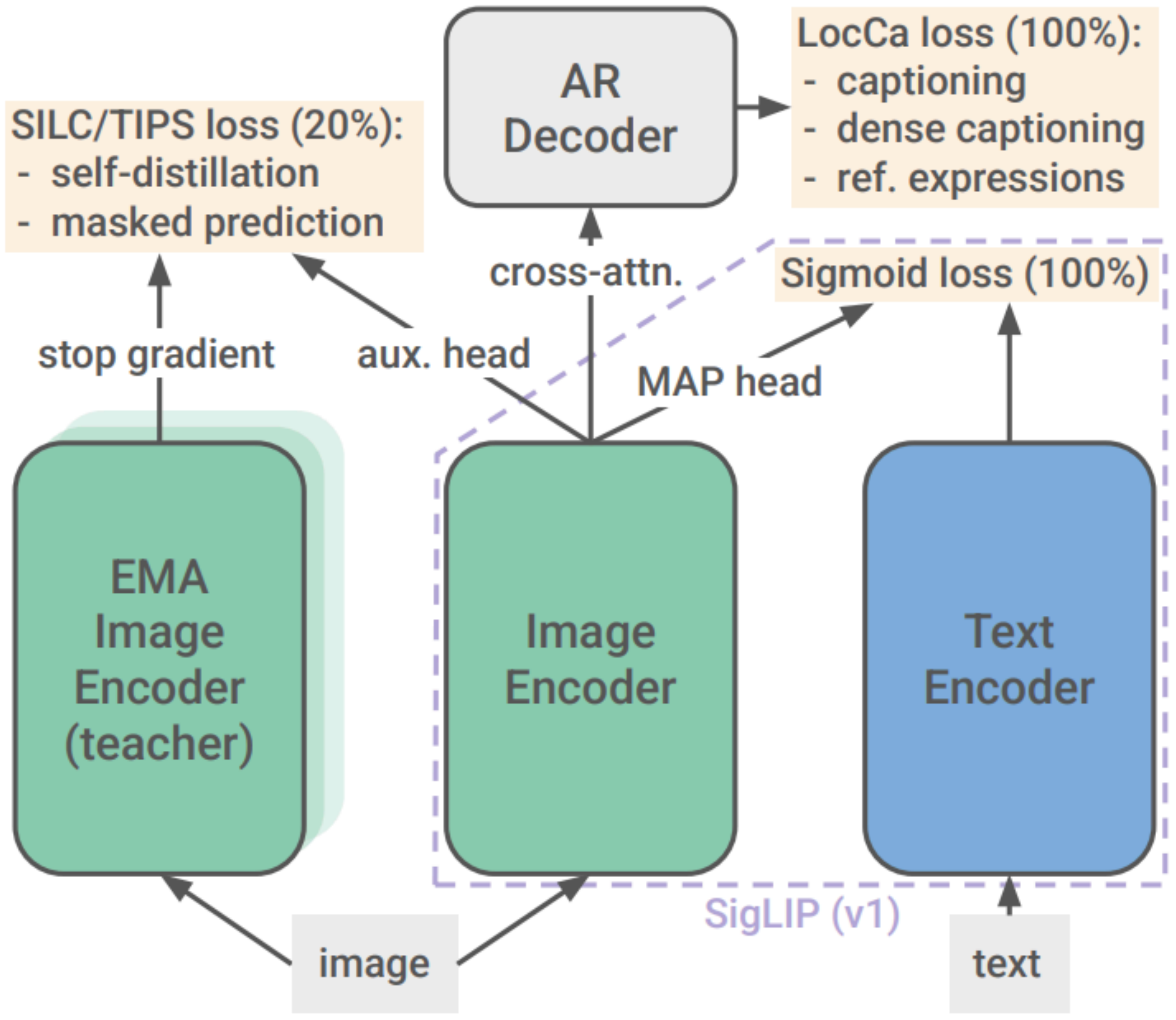


Figure 1 | SigLIP 2 adds the captioning-based pretraining from LocCa [62] as well as self-distillation and masked prediction from SILC [45] and TIPS [38] (during the last 20% of training) to the sigmoid loss from SigLIP [71]. For some variants, the recipe additionally involves fine-tuning with data curation [61] or adaptation to native aspect ratio and variable sequence length [6, 12].

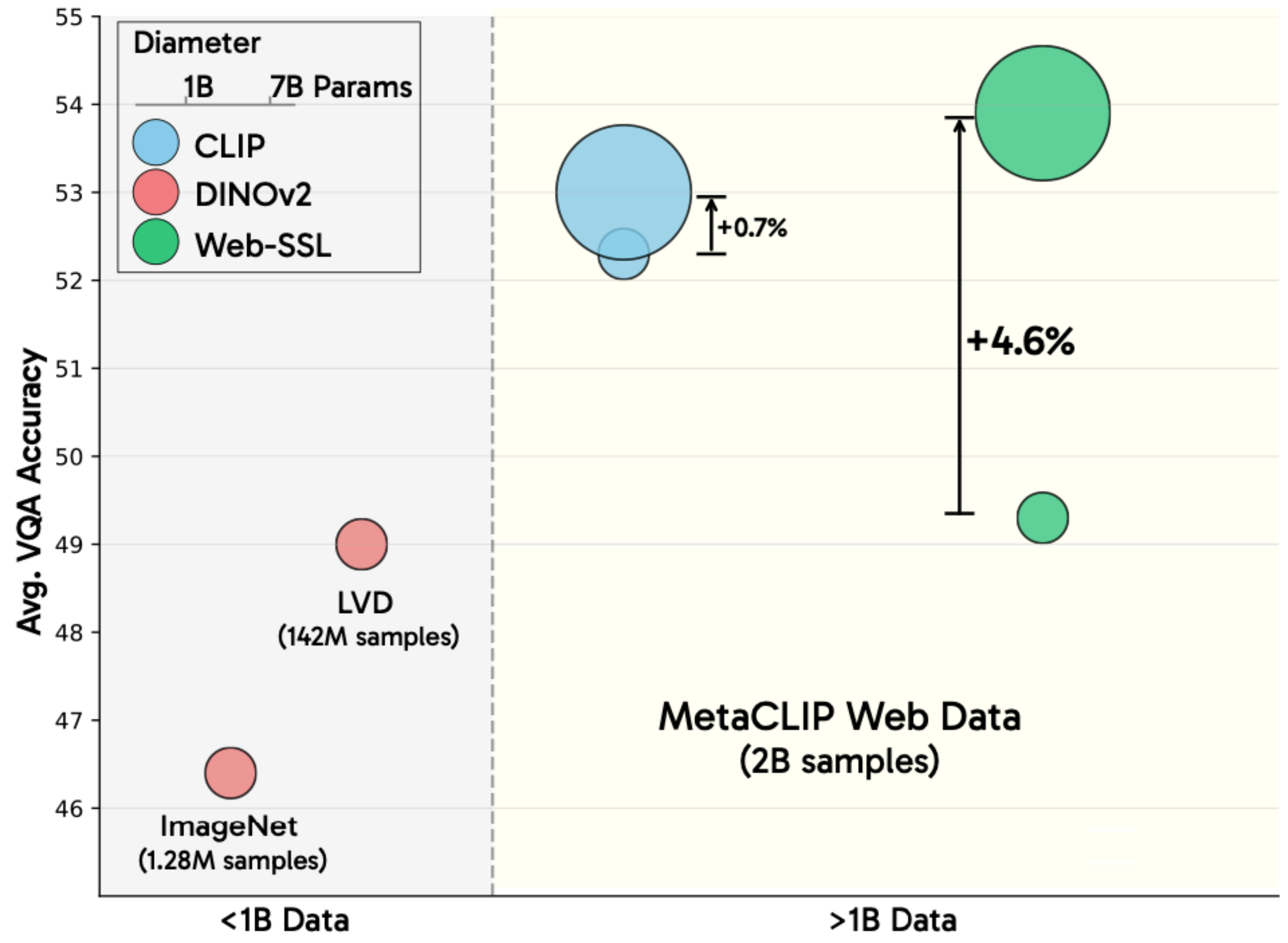


Figure 1 We compare the scaling behavior of visual SSL and CLIP on 16 VQA tasks from the Cambrian-1 suite under different data and model size regimes. Prior visual SSL methods achieved strong performance on classic vision tasks, but have underperformed as encoders for multimodal instruction-tuned VQA tasks. Our results show that with appropriate scaling of models and data, visual SSL can match the performance of language-supervised models across all evaluated domains—even OCR & Chart.

[1] SigLIP 2: Multilingual Vision-Language Encoders with Improved Semantic Understanding, Localization, and Dense Features, 2025
[2] Scaling Language-Free Visual Representation Learning, 2025

Other Good Works Out There

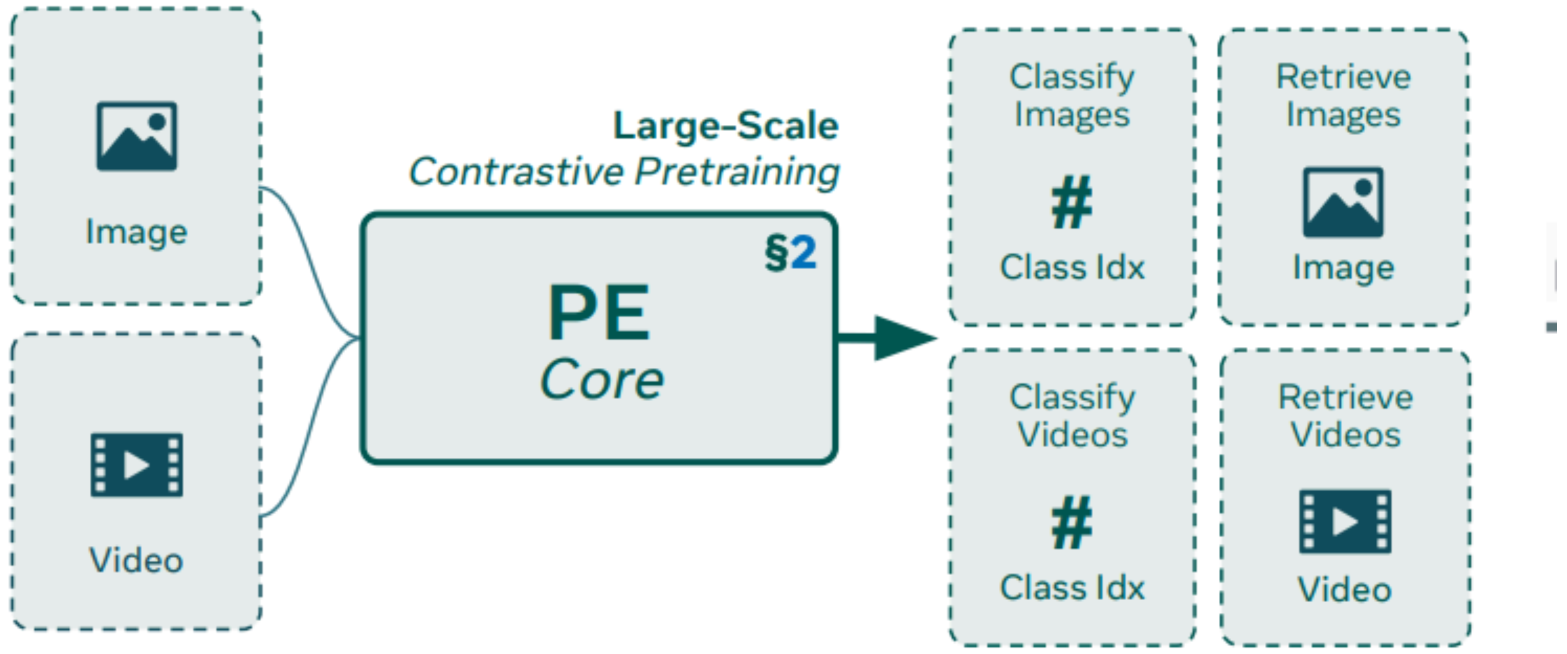


Figure 1 Perception Encoder (PE) is a family of larg

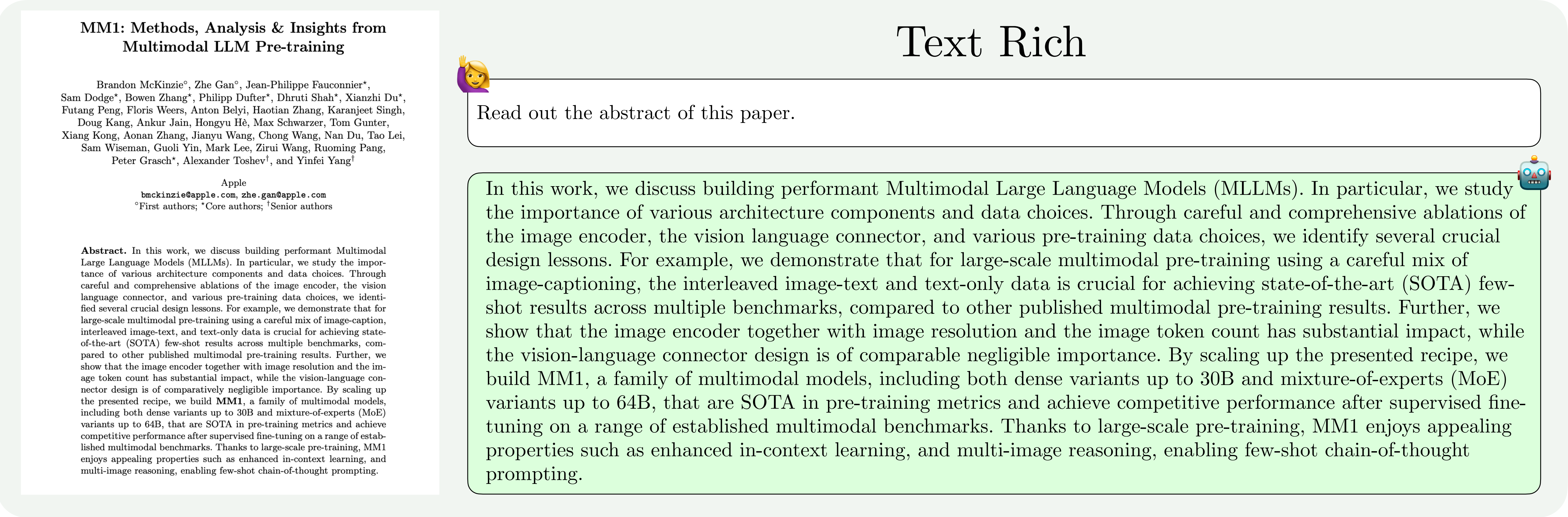
Figure 1: The *top* table compares our OpenVision series to OpenAI's CLIP and Google's SigLIP. The *bottom* figure showcases that OpenVision attain competitive or even superior multimodal performance than OpenAI's CLIP and Google's SigLIP.

[1] Perception Encoder: The best visual embeddings are not at the output of the network, 2025
[2] OpenVision : A Fully-Open, Cost-Effective Family of Advanced Vision Encoders for Multimodal Learning, 2025

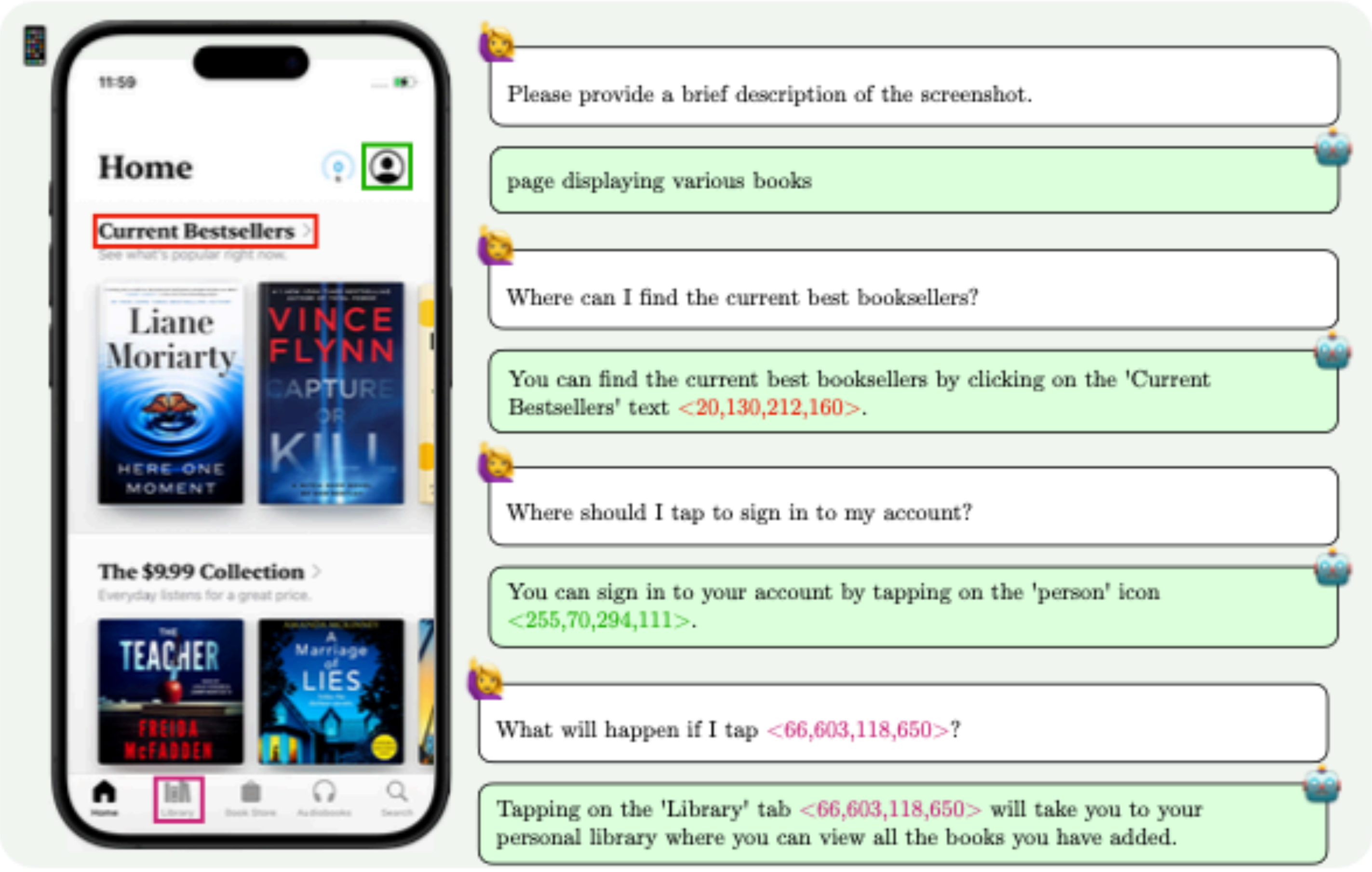
Understanding: Multimodal LLM

Core Vision Capabilities (Examples from MM1.5)

Text-rich image understanding

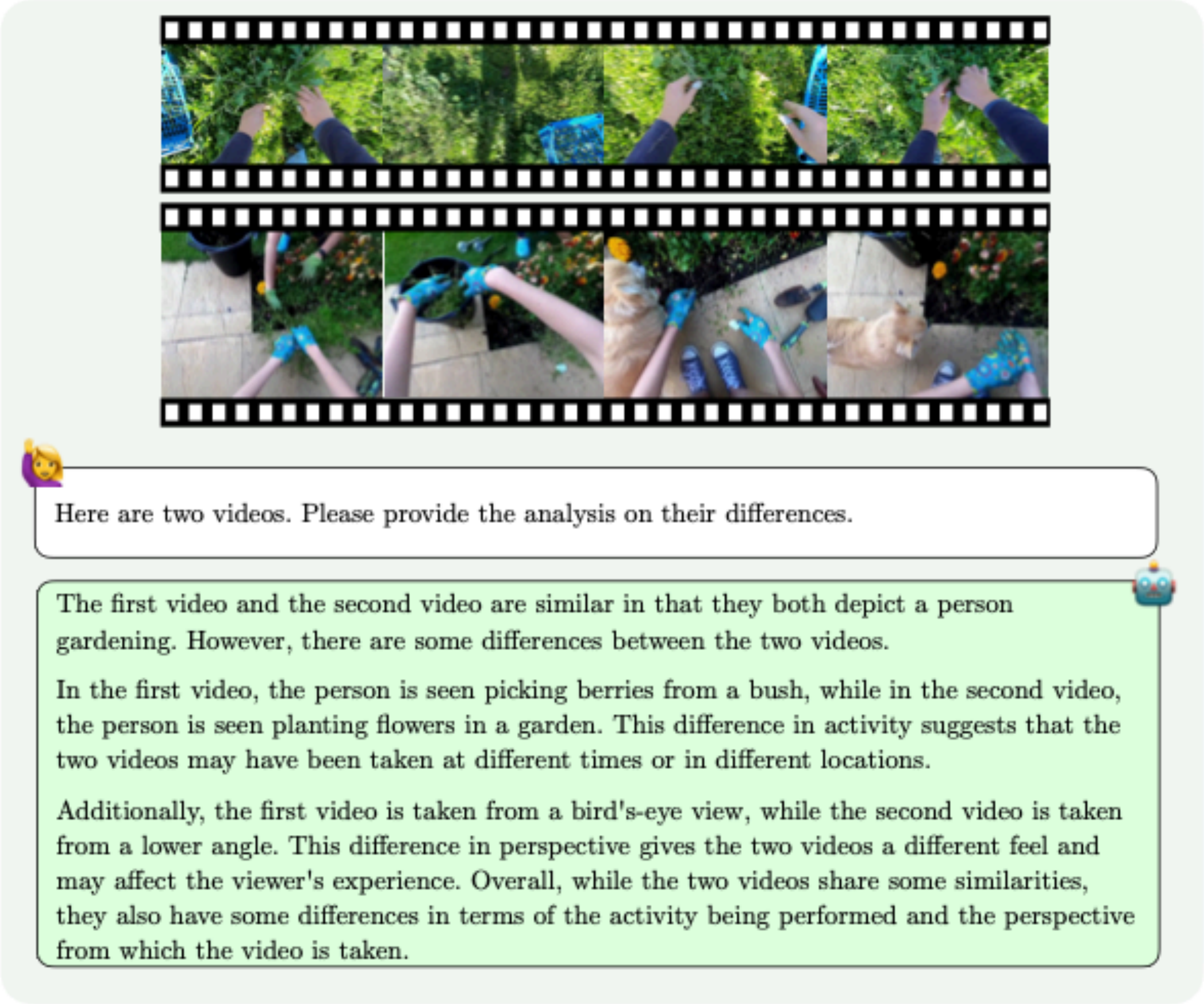


UI understanding



Referring & Grounding

Video understanding



Core Vision Capabilities (Examples from MM1.5)

Multi-Image

Help me generate a Twitter post providing these images.

Step 1: Identify the main subject of each image.

- Image 1: The main subject is a crowd of people at a concert.
- Image 2: The main subject is the Sagrada Familia, a large Gothic-style church in Barcelona.
- Image 3: The main subject is a cup of coffee with a heart-shaped foam design.

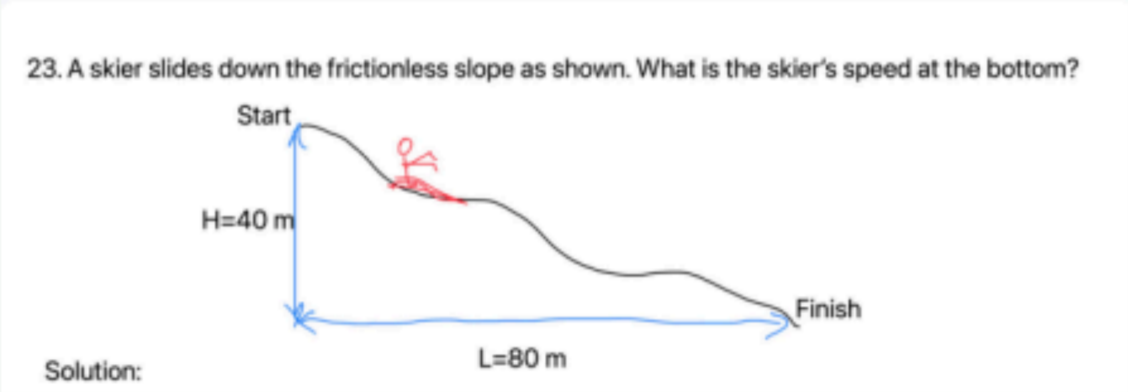
Step 2: Determine the tone and theme of each image.

- Image 1: The tone is energetic and lively, with a focus on the vibrant atmosphere of a concert.
- Image 2: The tone is historical and architectural, showcasing the grandeur of the Sagrada Familia.
- Image 3: The tone is cozy and inviting, with a focus on the comforting act of enjoying a cup of coffee.

Step 3: Craft a Twitter post that incorporates the main subject and tone of each image.

"Experience the energy of a live concert at [Concert Venue] or take a moment to appreciate the architectural beauty of [Sagrada Familia] with [Tourist Attraction]. Enjoy a warm cup of coffee with a heart-shaped foam design from [Coffee Shop]."

Math/Reasoning



Try to reason about the question step by step.

To find the skier's speed at the bottom, we can use the conservation of energy principle. At the start, the skier has potential energy, and at the end, the skier has kinetic energy. Since the energy is conserved, we can set up the following equation:

Start: $E = mgh$ End: $E = (1/2)mv^2$

where E is the energy, m is the mass of the skier, g is the acceleration due to gravity (9.81 m/s^2), h is the height, and v is the final velocity.

We are given the initial height (40 m) and the final height (0 m) since the skier reaches the ground. We can plug these values into the equation and solve for the final velocity (v):

$(1/2)mv^2 = mgh$

Divide both sides by m:

$(1/2)v^2 = gh$

Now, plug in the given values for g and h:

$(1/2)v^2 = (9.81m/s^2)(40m)$

$(1/2)v^2 = 392.4J$

Multiply both sides by 2:

$v^2 = 784.8J$

Now, take the square root of both sides to find the final velocity (v):

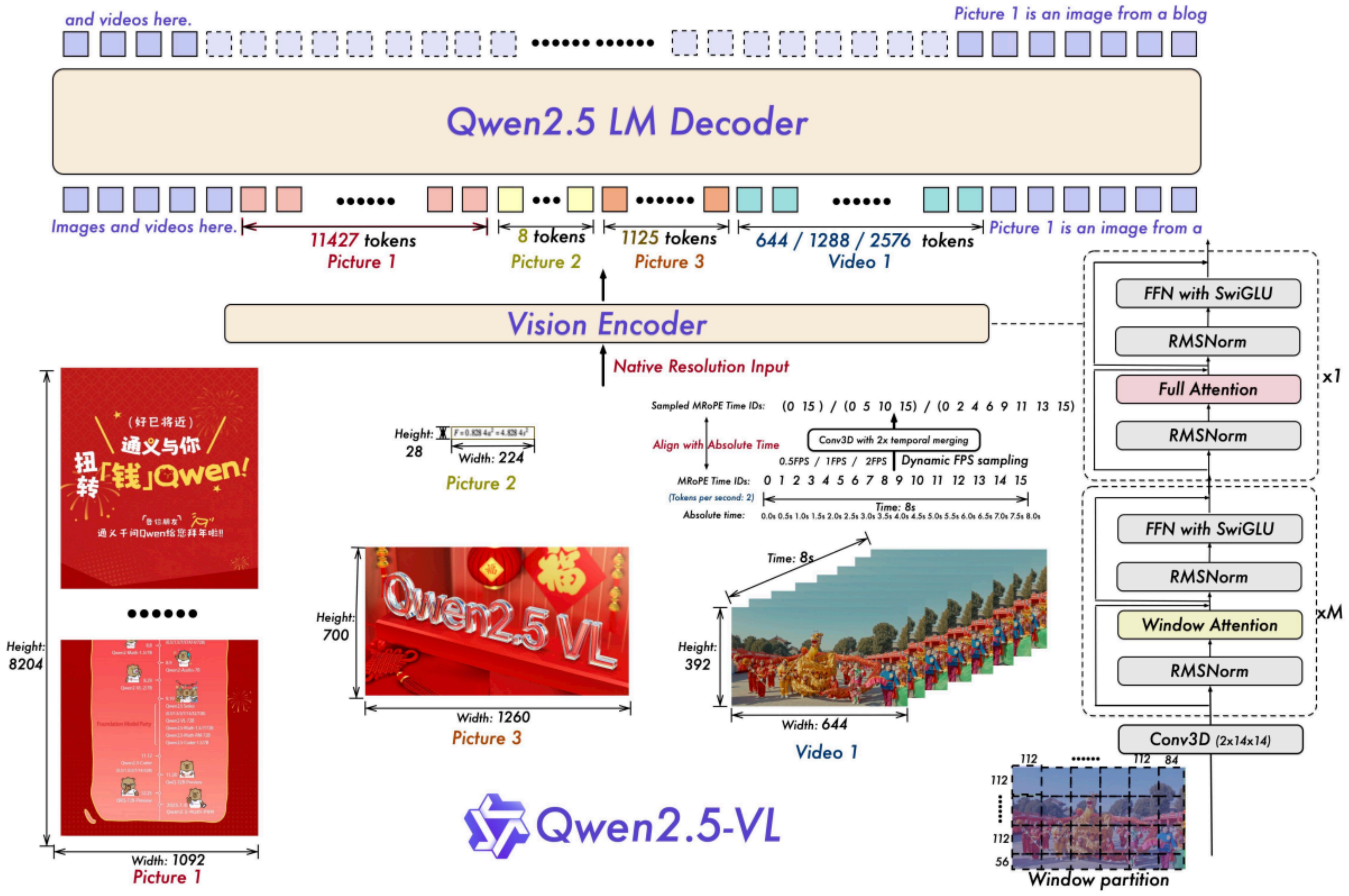
$v = \sqrt{784.8J}$

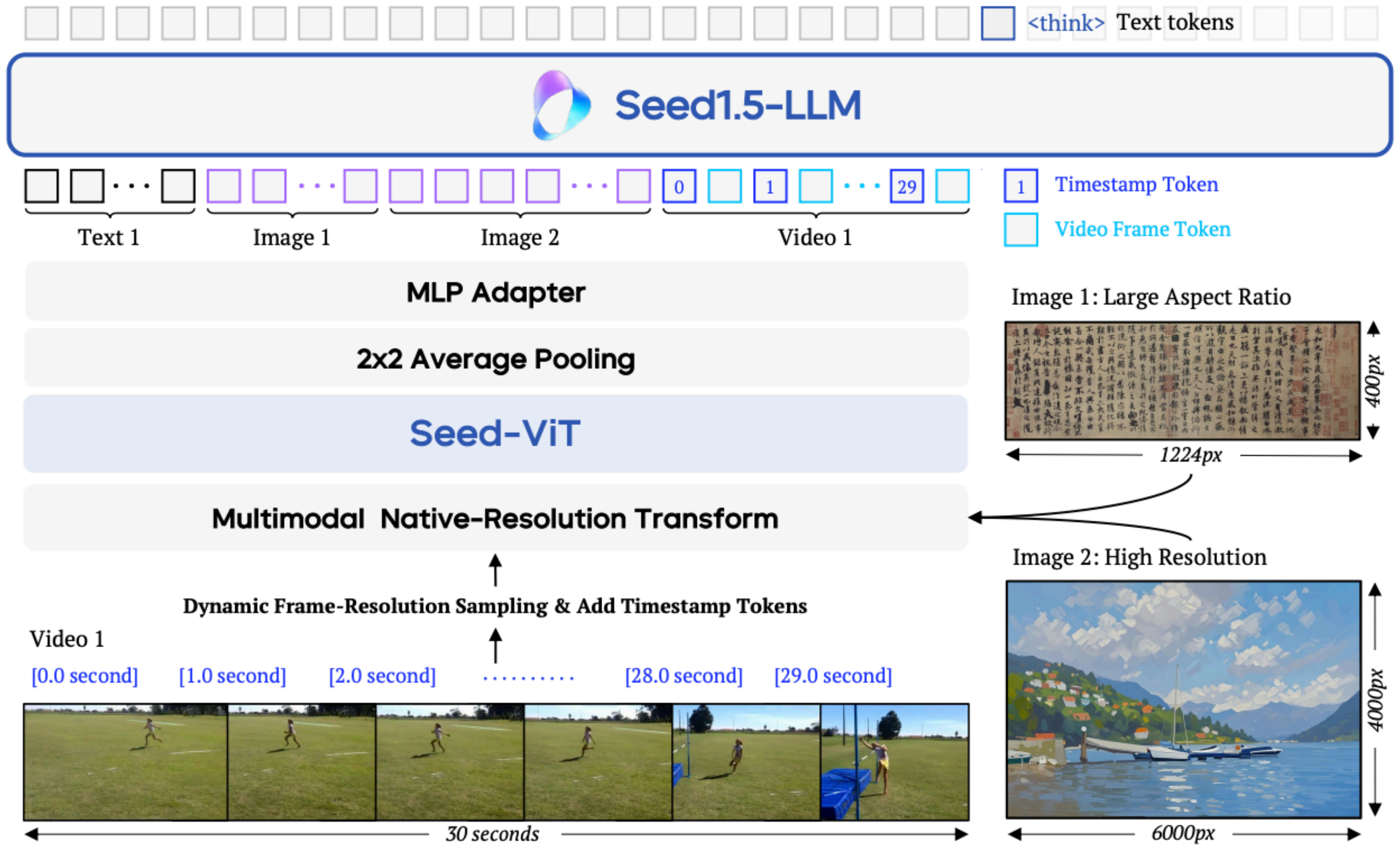
$v \approx 28m/s$

So, the skier's speed at the bottom is approximately 28 m/s.

Qwen2.5-VL vs. Seed1.5-VL

- Modern multimodal LLMs look increasingly similar
- It's all about data, no matter it's text-rich, UI, or video understanding

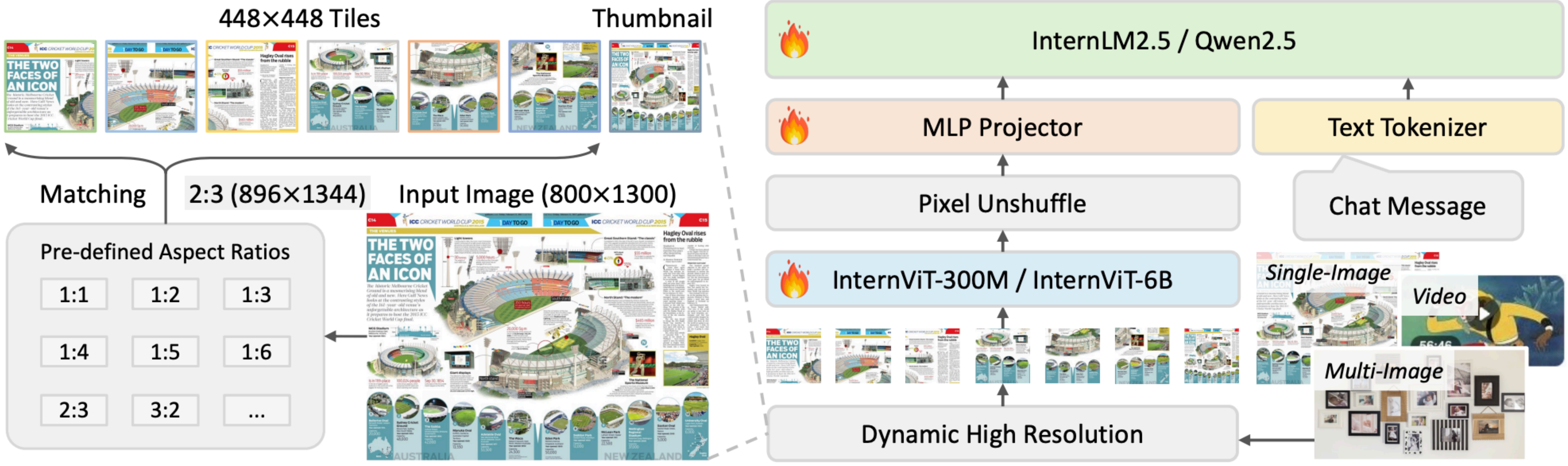




[1] Qwen2.5-VL Technical Report, 2025
[2] Seed1.5-VL Technical Report, 2025

Example 1: Text-rich Image Understanding (InternVL-2.5)

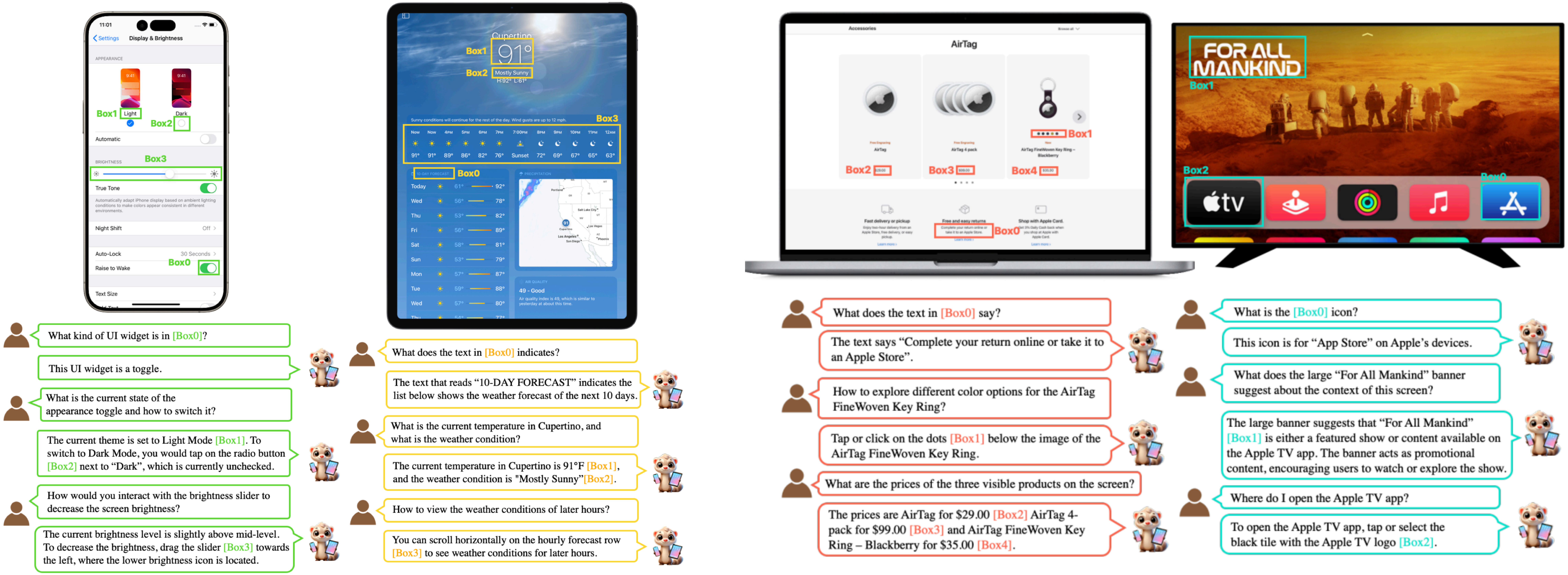
- Native resolution support as in Qwen2.5-VL using NaViT like methods
- High-resolution support via dynamic image splitting as in InternVL-2.5 and many others



(a) Data Preprocessing (b) Model Architecture

Example 2: UI Understanding (Ferret UI 2)

- GUI grounding and navigation becomes an increasingly hot topic
- Many good works out there, e.g., U-Ground, Show-UI, UI-TARS and all recent R1-like methods



Example 3: How About Egocentric Intelligence?

“What can I see?” — Long Video Understanding

“Where did I leave my phone?” — Long Video Memory

Interaction

Video shot by Vision Pro

MM-Ego: Data

Human Annotated Narrations
from existing dataset (Ego4D)

Video Clip 1: “I sit down on the sofa.”

Video Clip 2: “I put the wallet and phone on the table.”

Text-only LLM

Prompt: “Design a question about visual details based on the narrations.”

Memory QA

Video: [Video Clip 1, Video Clip 2, Video Clip 3]

Question: “Given this video, where did I leave my phone?”

Answer: “I left my phone on the table.”

Long Video Memory Dataset

Conversation counts

- Train split: 942 K
- Test split: 32 K

Question counts

- Train split: 7 M
- Test split: 235 K

Long Video Understanding Dataset

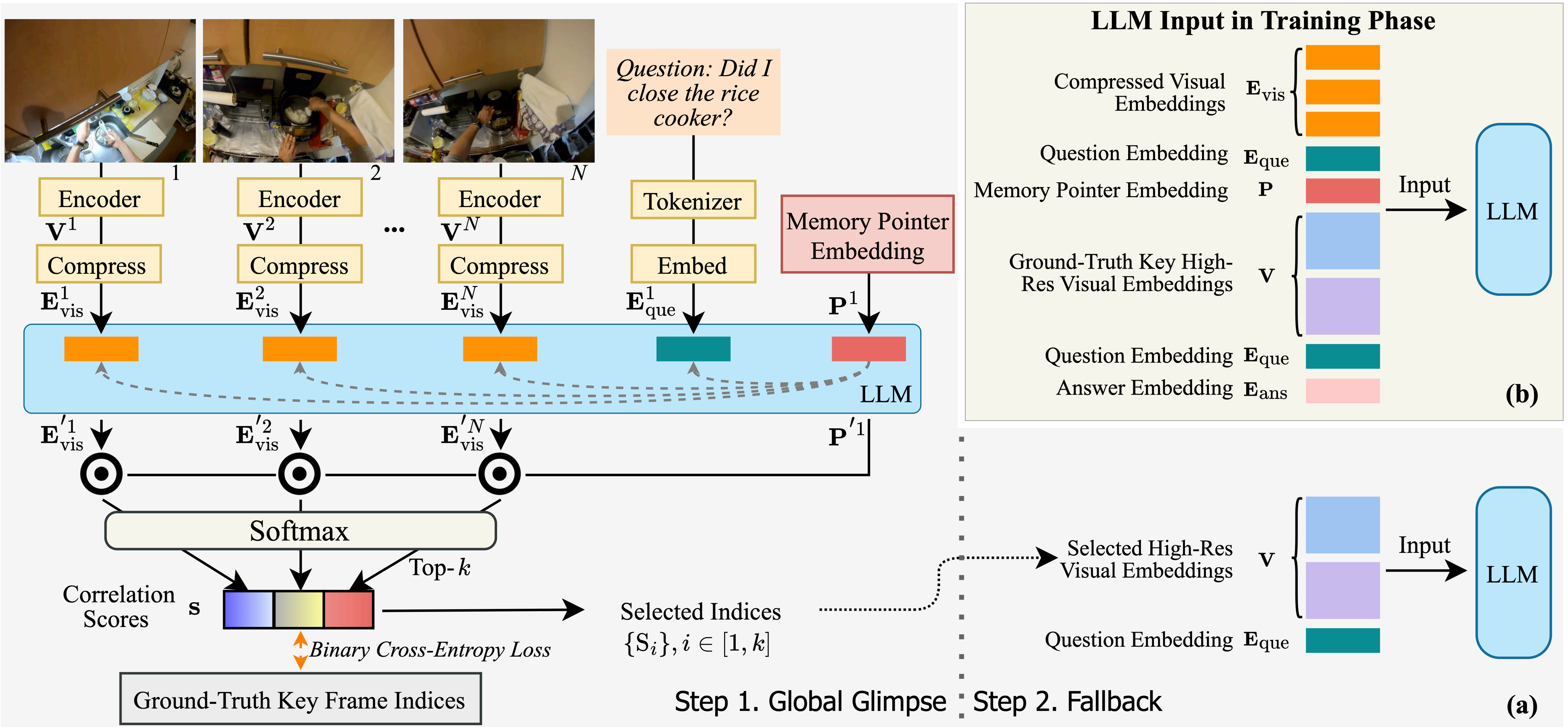
- Conversation/Question counts
- Train split: 999k

Q: Which hand did the man place on his chest?
A: The man placed both hands on his chest.

Q: What did I do with the pear aft er slicing it?
A: I moved the pear on the tray w ith the knife in my right hand.

MM-Ego: Model Architecture

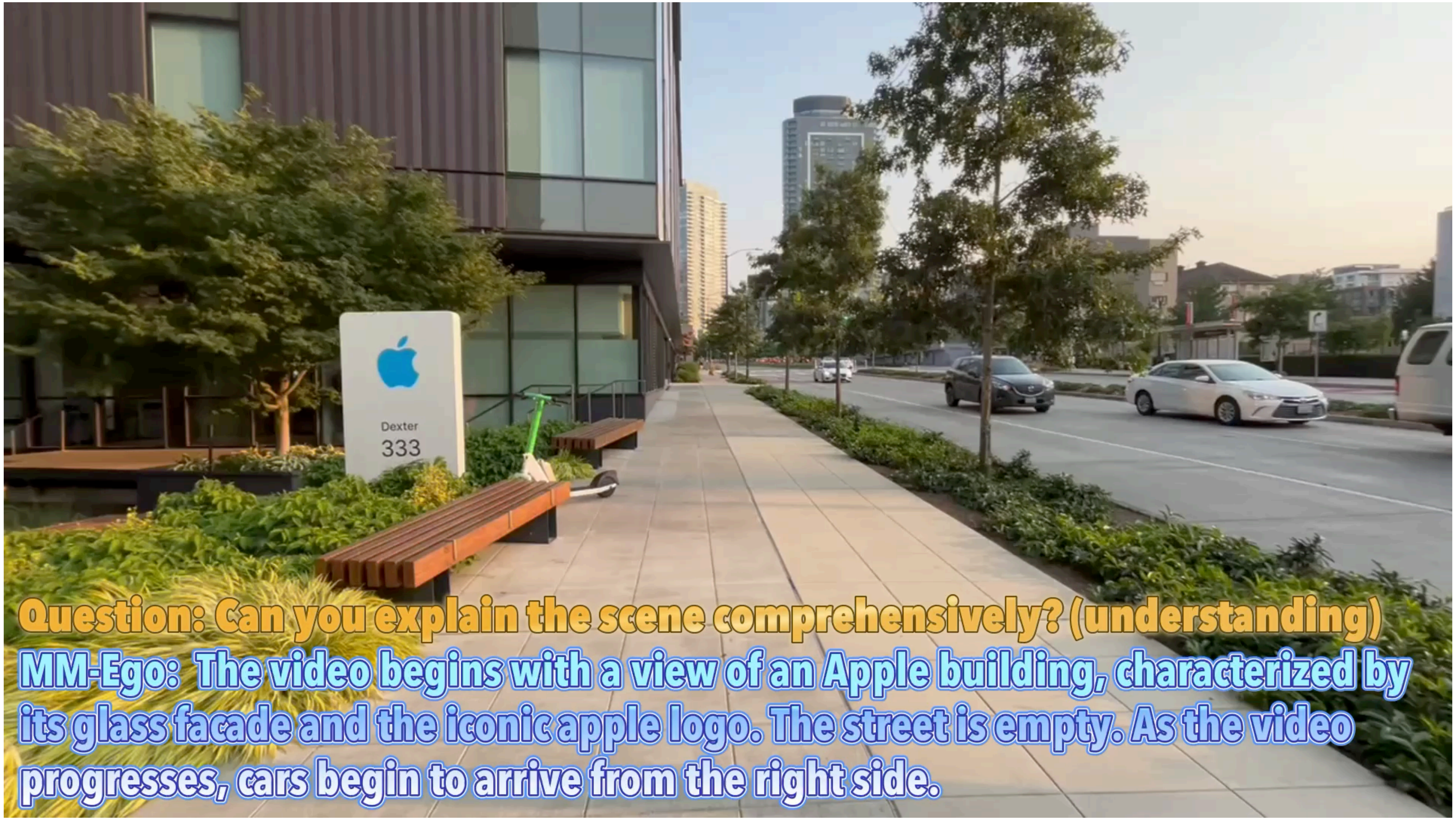
- Memory Pointer Prompting



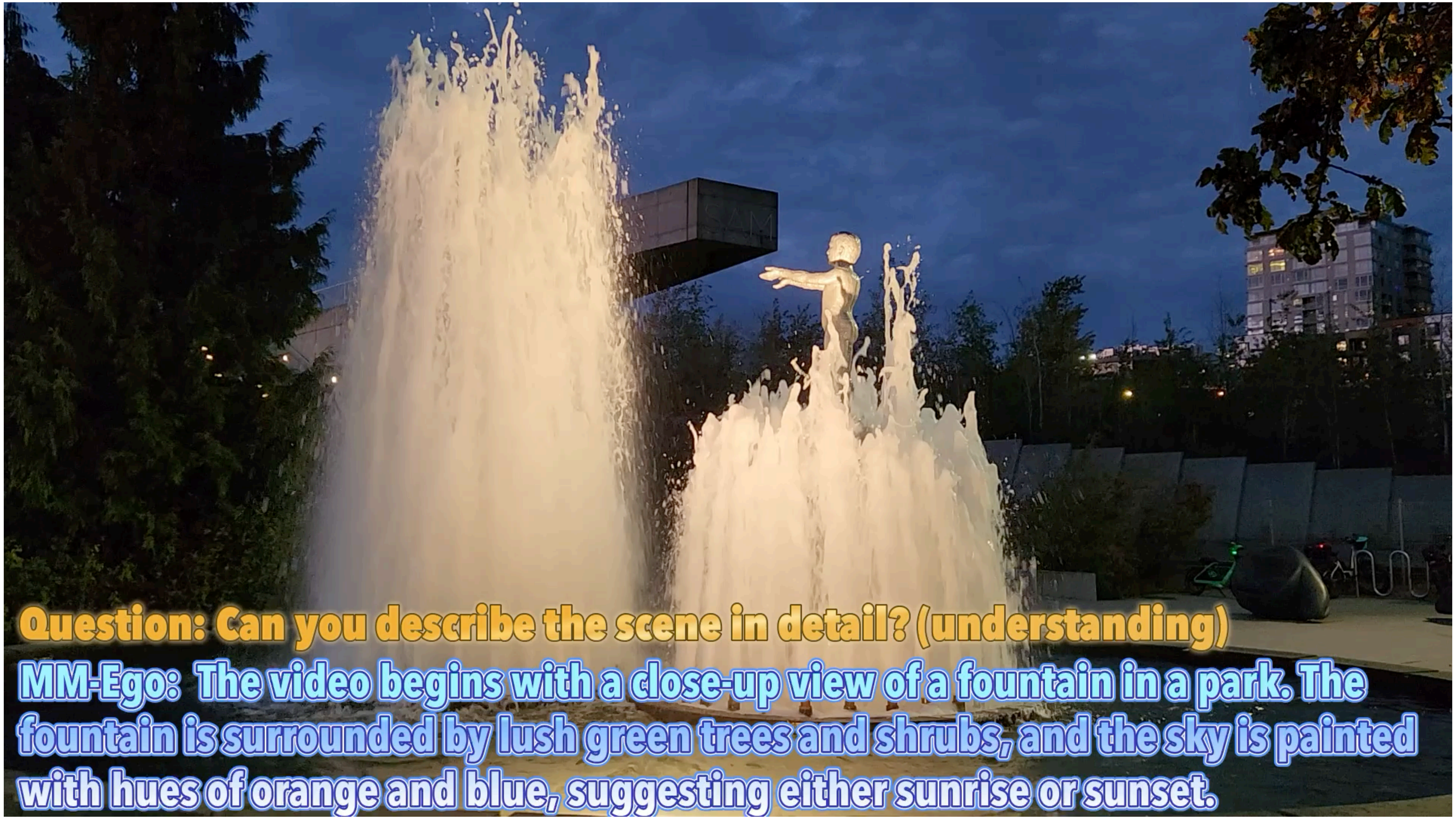
Global Glimpse - the correlation scores between the memory pointer and all compressed visual embeddings

Fallback - high-resolution visual embeddings corresponding to the selected indices

MM-Ego: Apple Office at Seattle

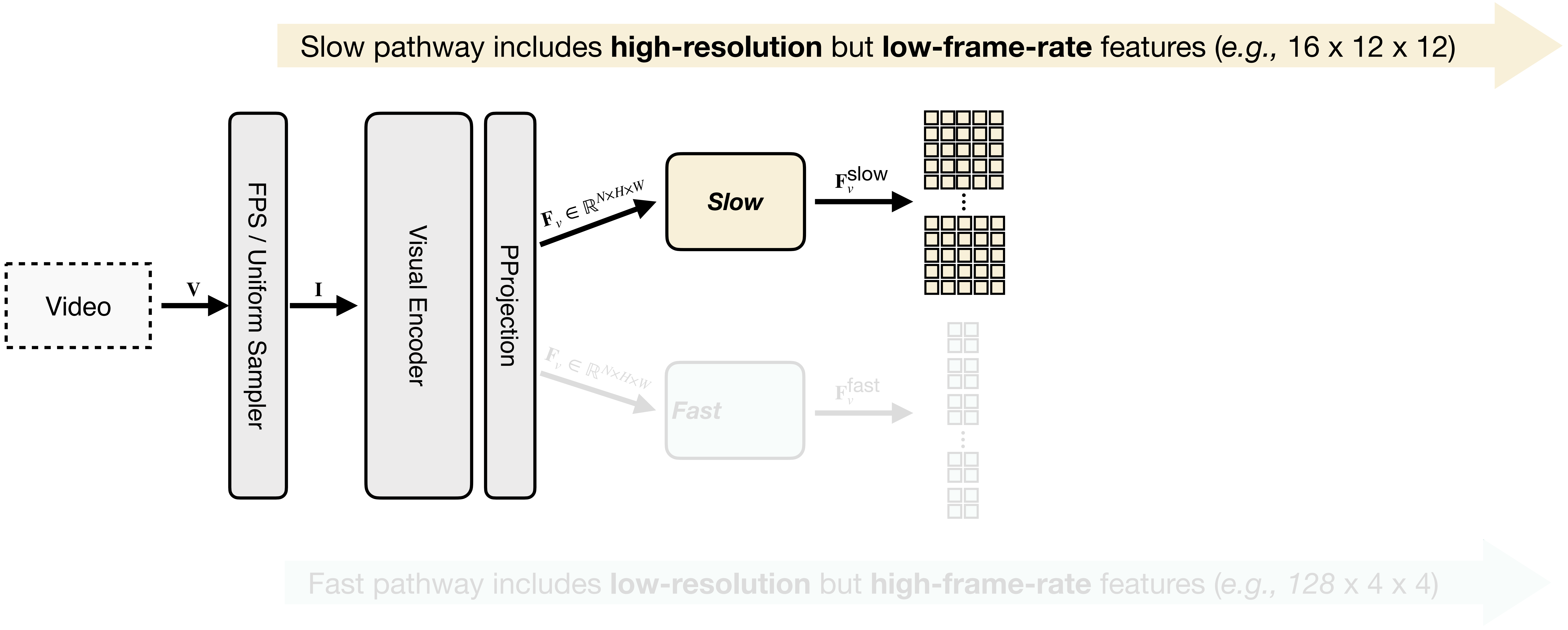


MM-Ego: Another View from Seattle



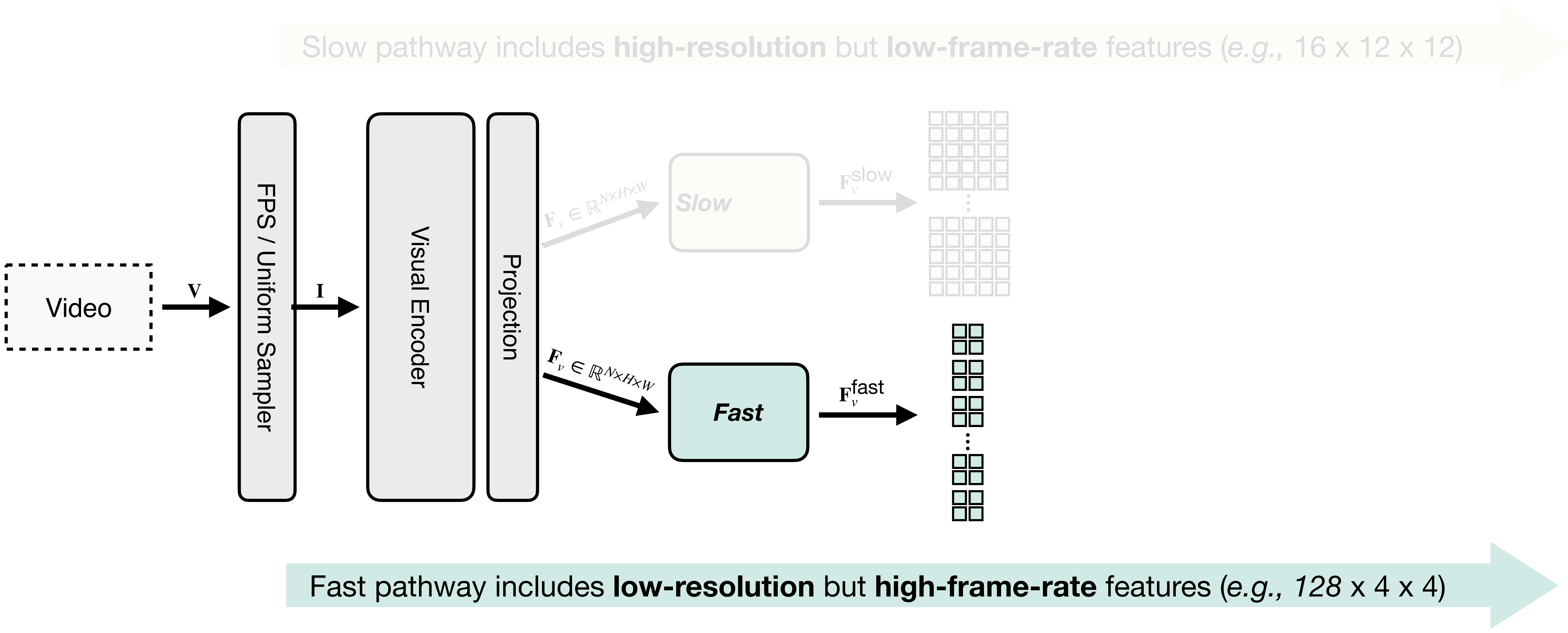
Slow Fast Thinking for Video Understanding

- Slow pathway deals with high-resolution features



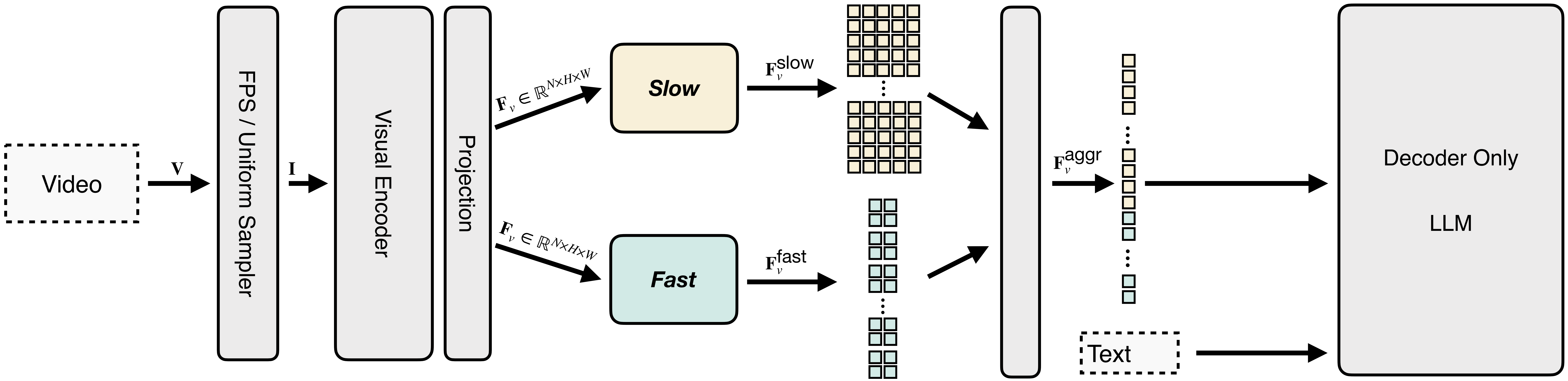
Slow Fast Thinking for Video Understanding

- Fast pathway deals with high-frame-rate features



Slow Fast Thinking for Video Understanding

- SlowFast-LLaVA-1.5 achieves strong performance across all image and video benchmarks when trained on the joint SFT mixture



Video Results: 3B Models

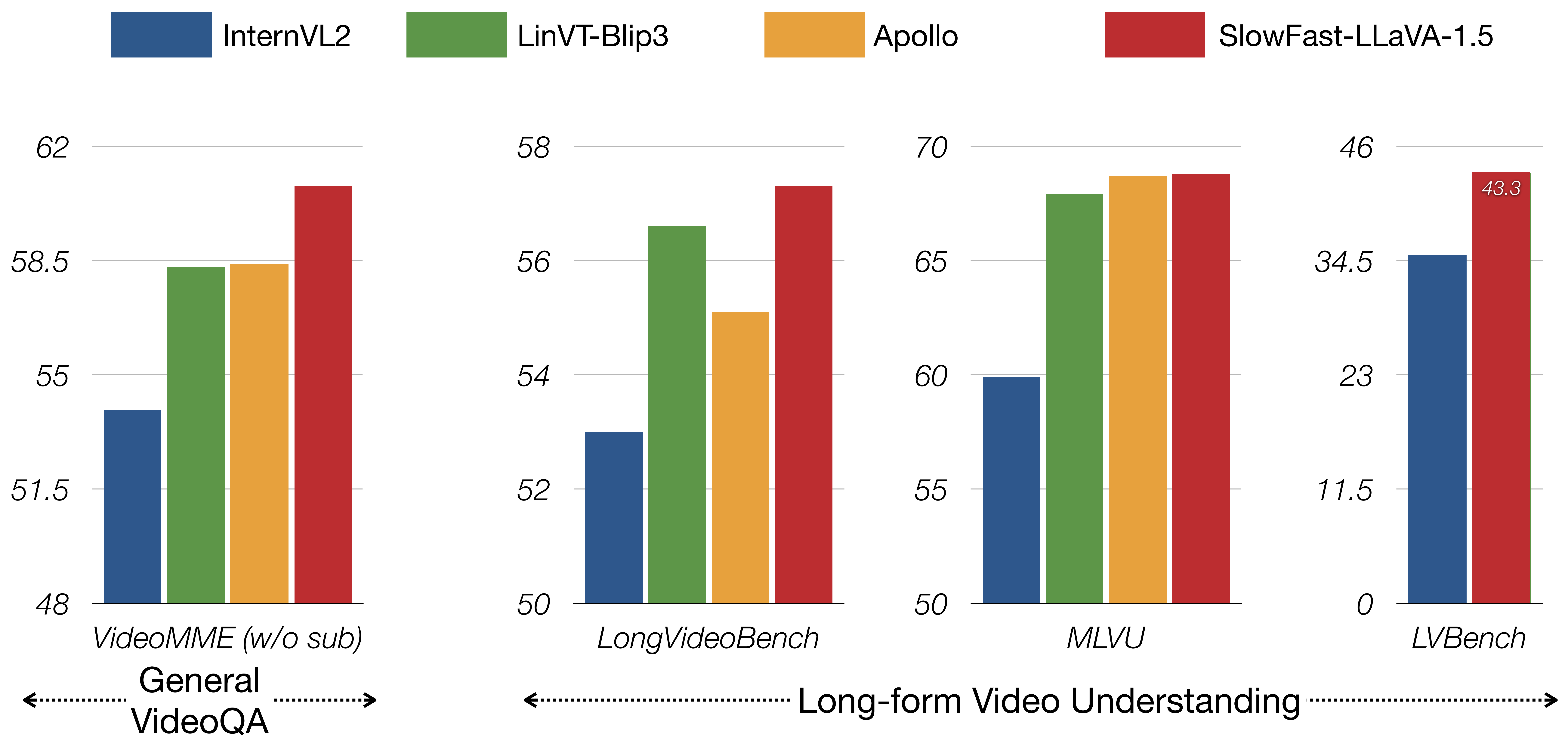
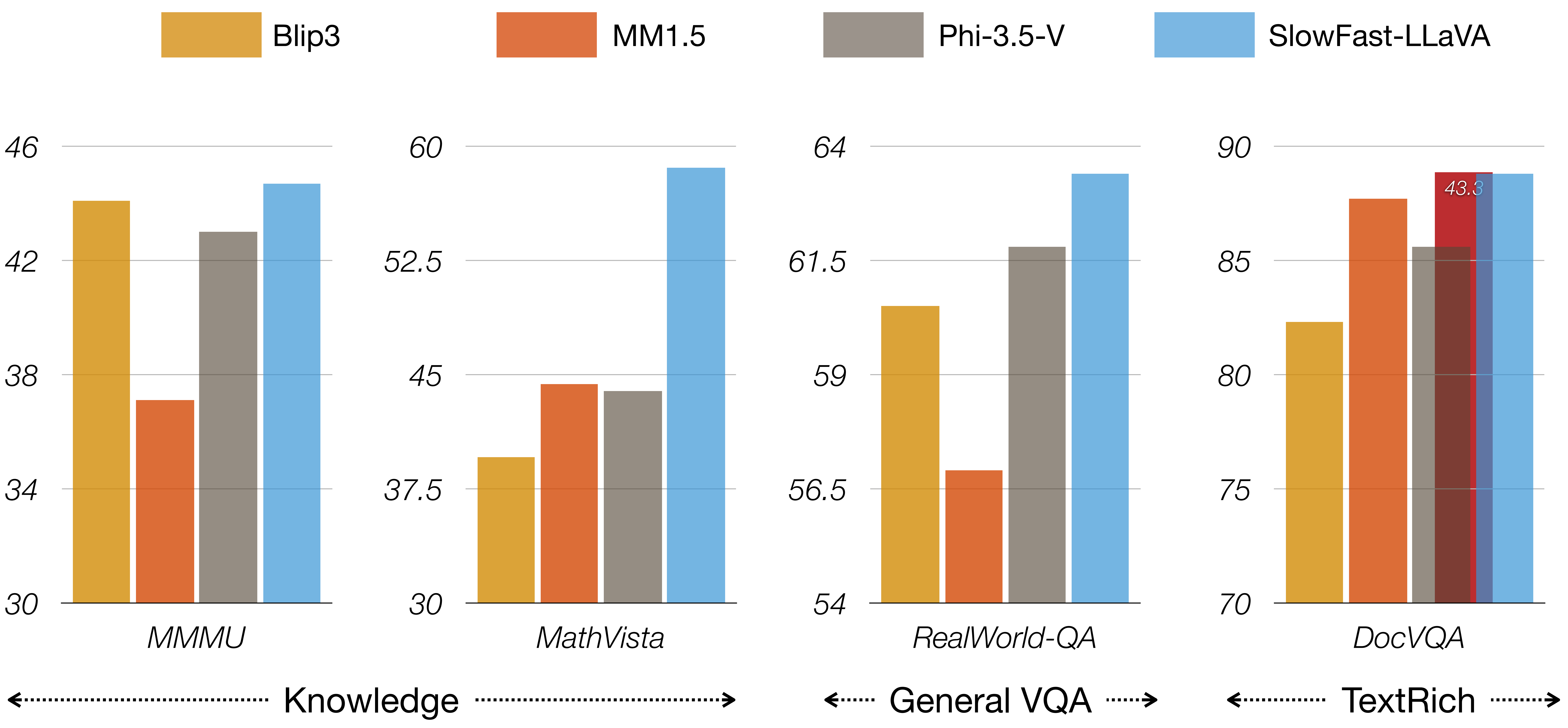
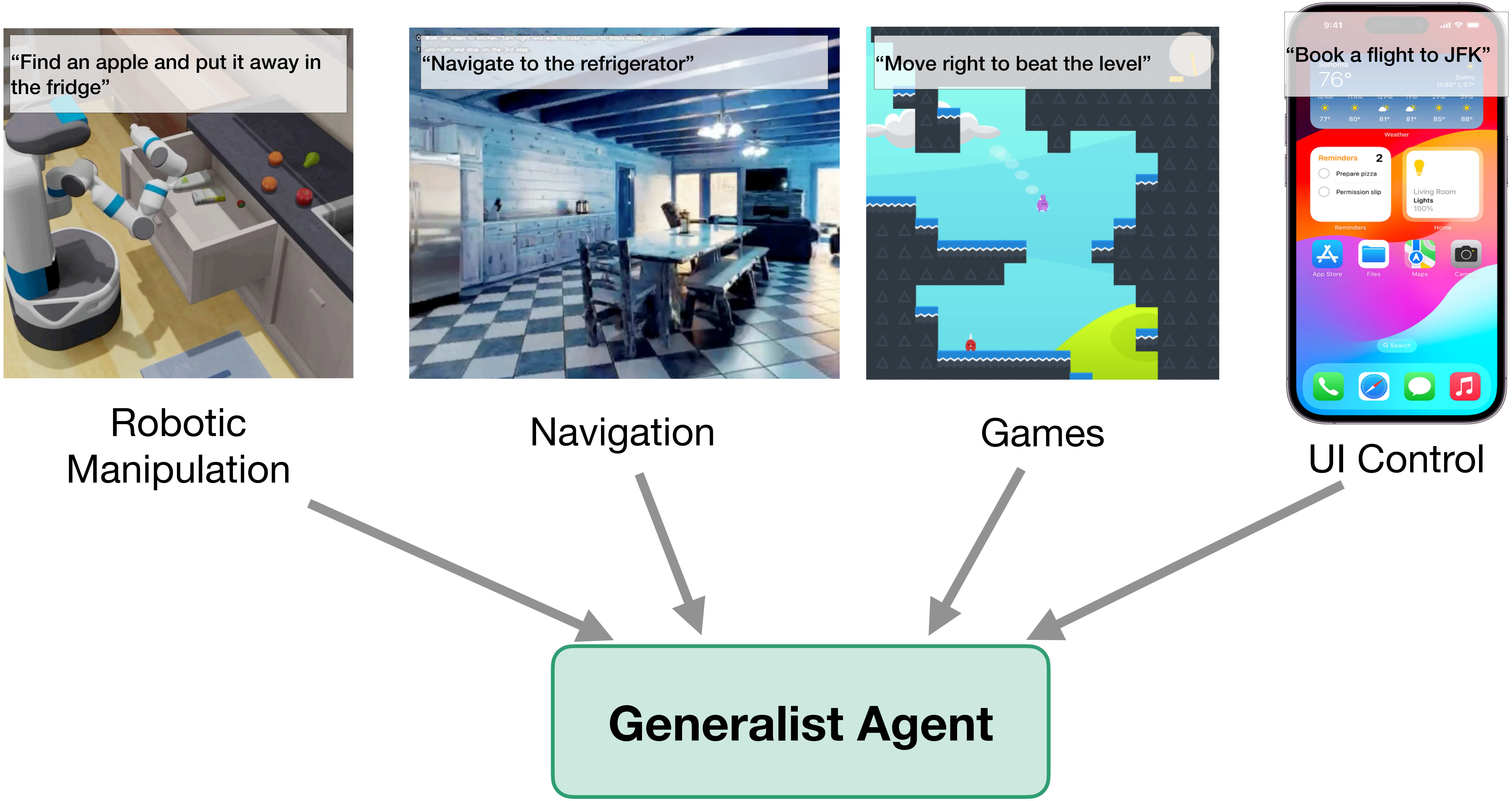


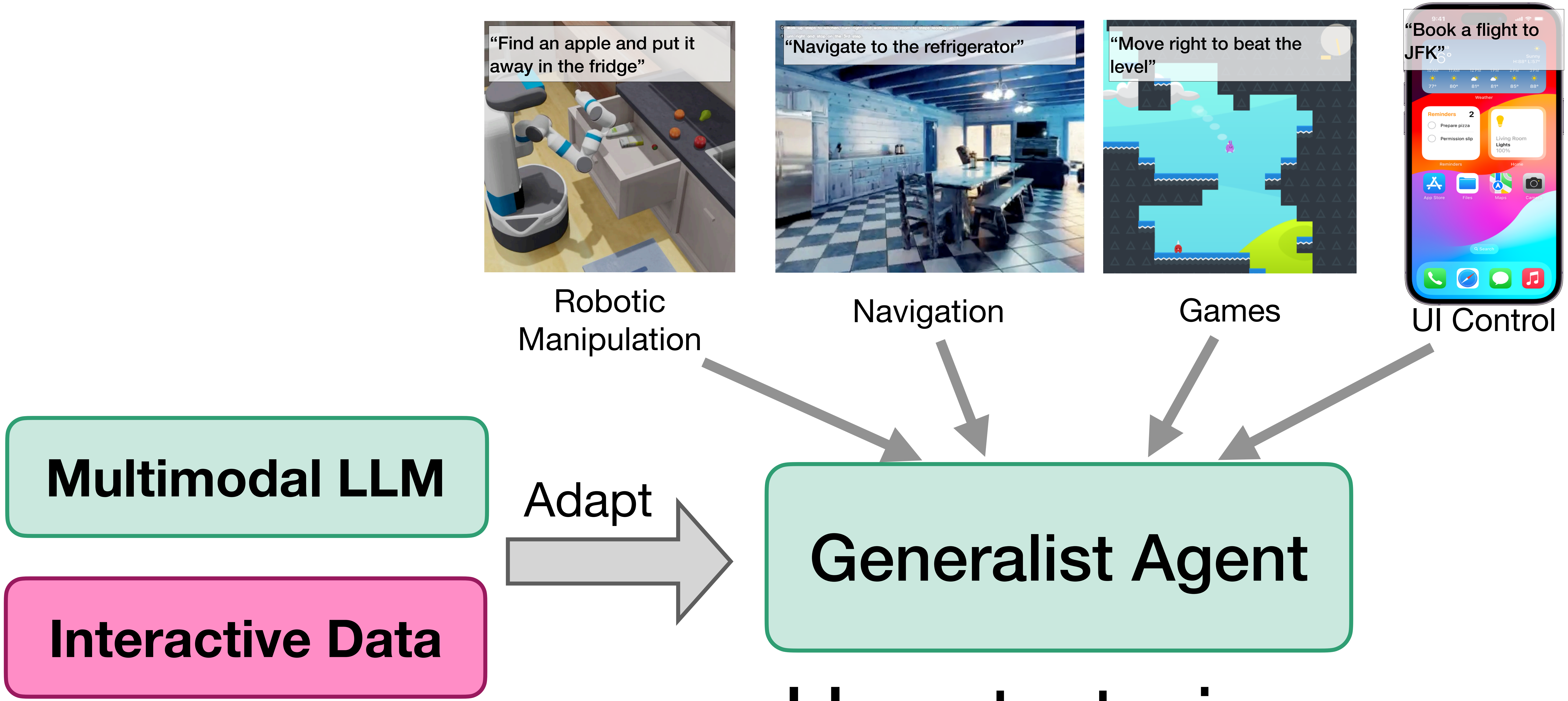
Image Results: 3B Models



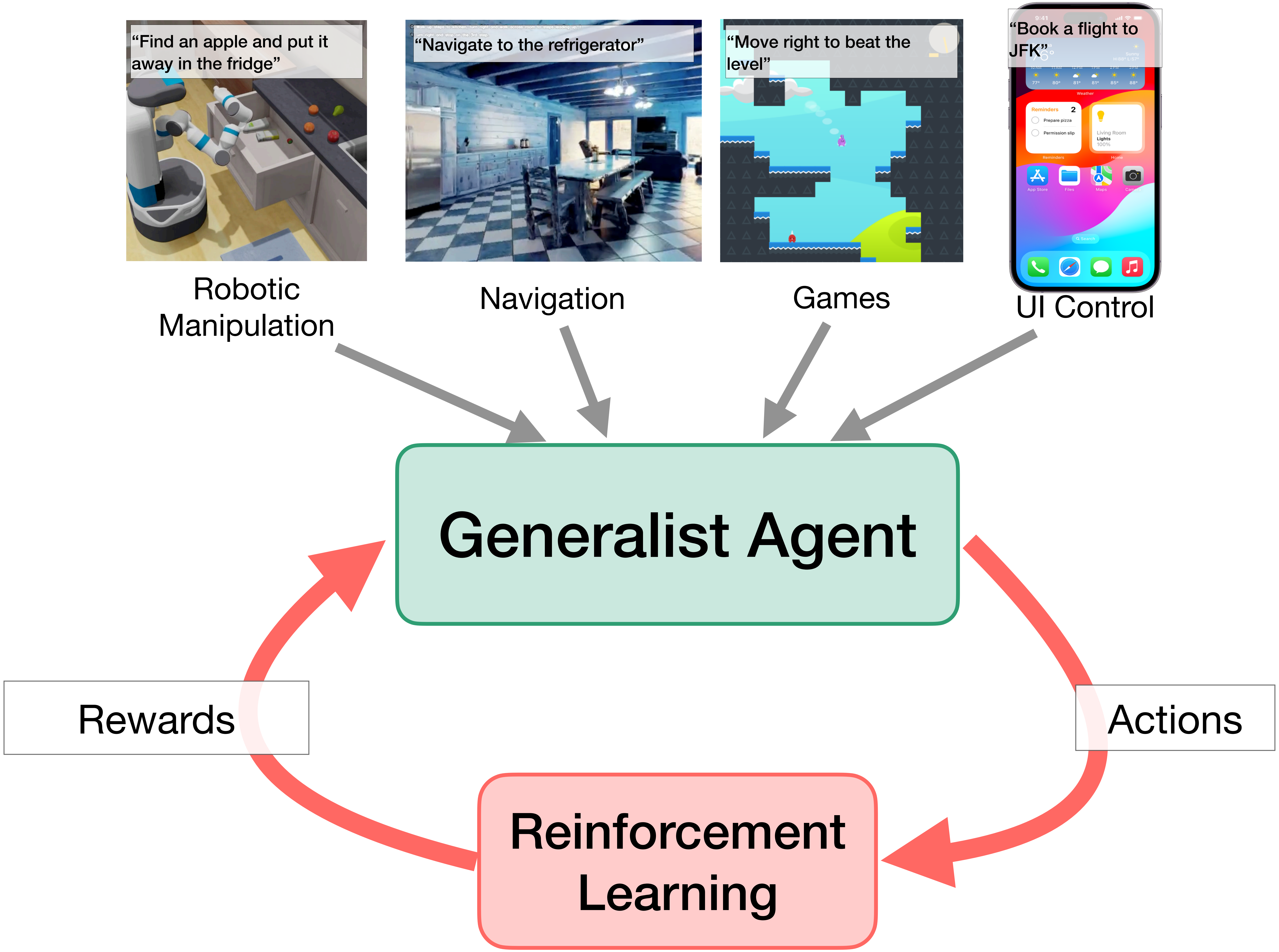
Acting: Multimodal Agent

Slides in this section are from Andrew Szot

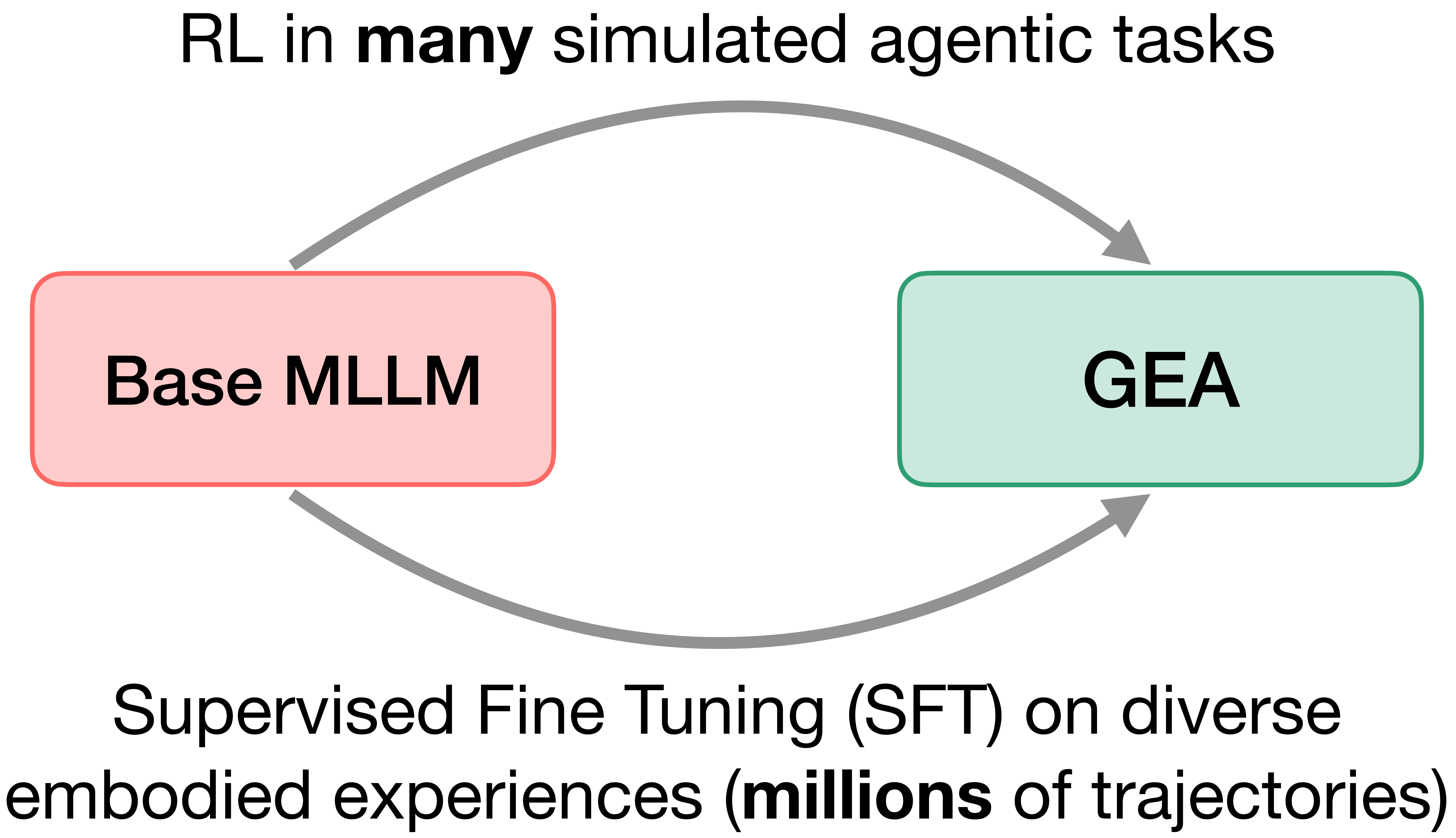

"Find an apple and put it away in the fridge"
"Navigate to the refrigerator"
"Move right to beat the level"
"Book a flight to JFK"
Robotic Manipulation
Navigation
Games
UI Control
Generalist Agent



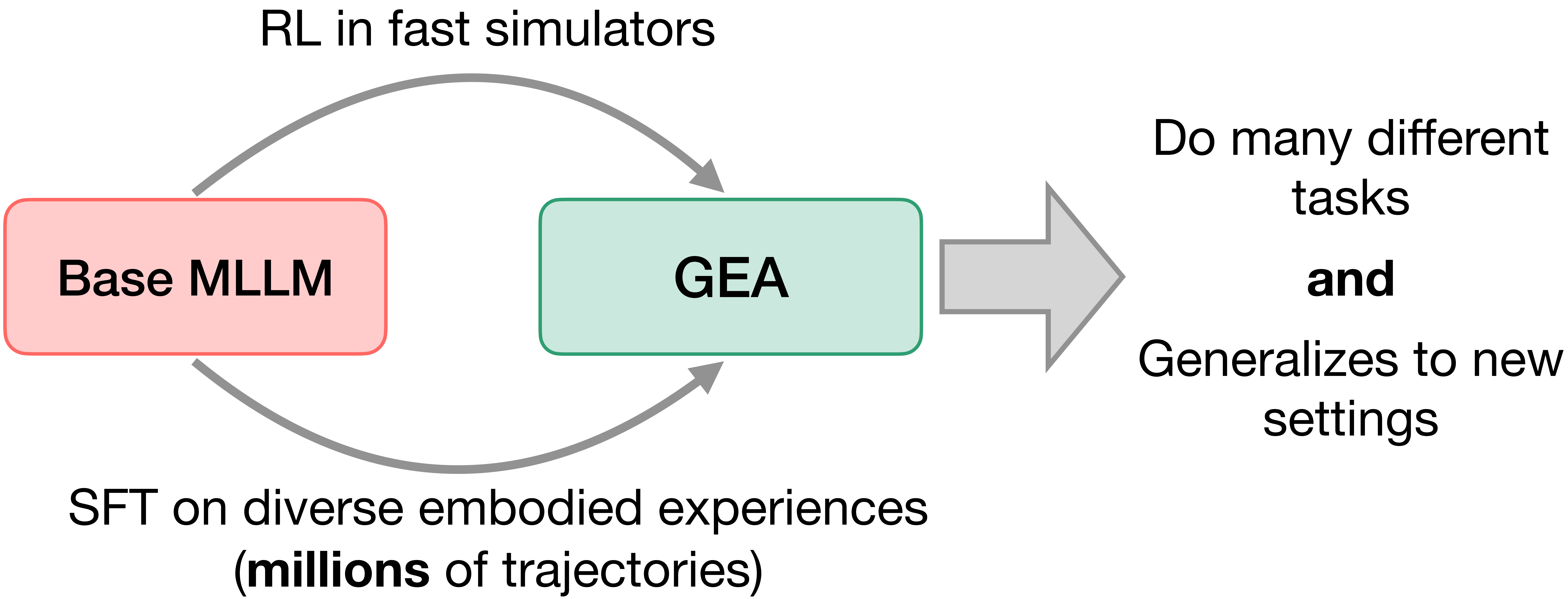
How to train a generalist agent?


"Find an apple and put it away in the fridge"
Robotic Manipulation
"Navigate to the refrigerator"
Navigation
"Move right to beat the level"
Games
"Book a flight to JFK"
UI Control
Generalist Agent
Rewards
Actions
Reinforcement Learning

Generalist Embodied Agent (GEA)



Generalist Embodied Agent (GEA)

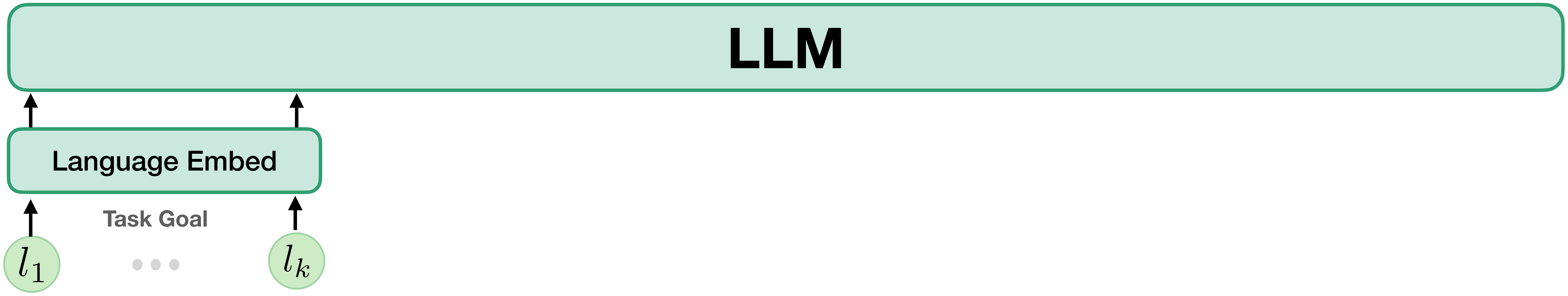


GEA Architecture

Start with a pretrained MLLM

GEA Architecture

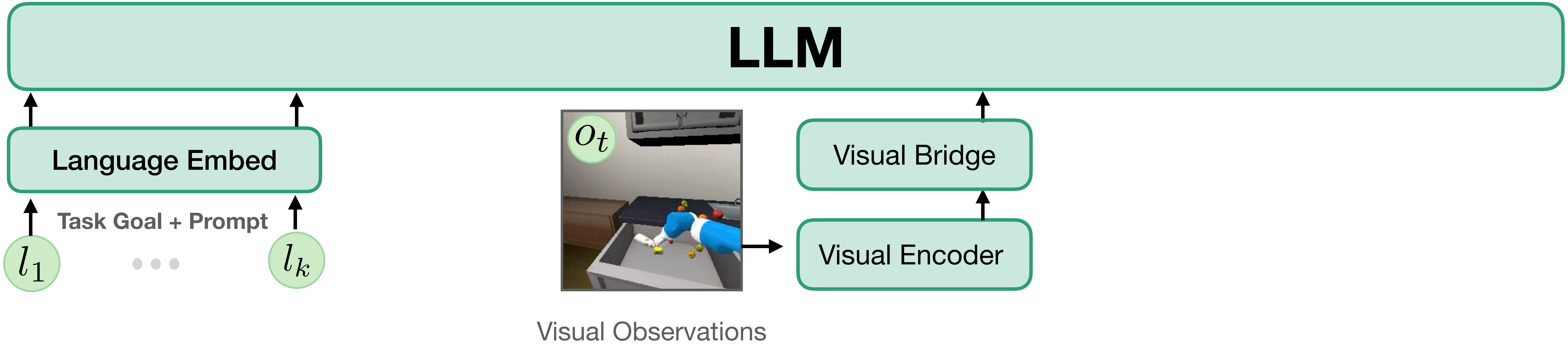
Tokenize and input task instruction to MLLM



Task Instruction: “Move all the fruit to the fridge”

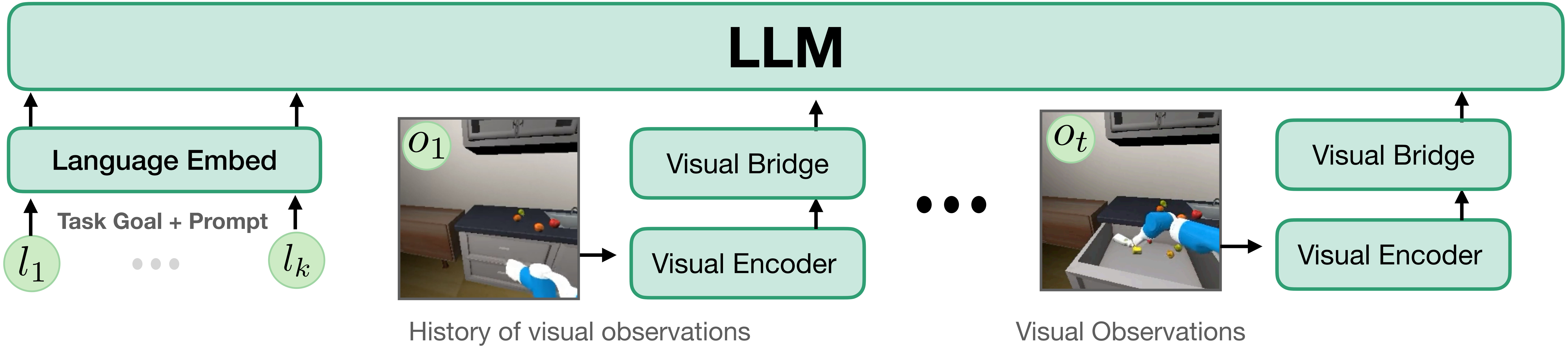
GEA Architecture

Encode visual observations



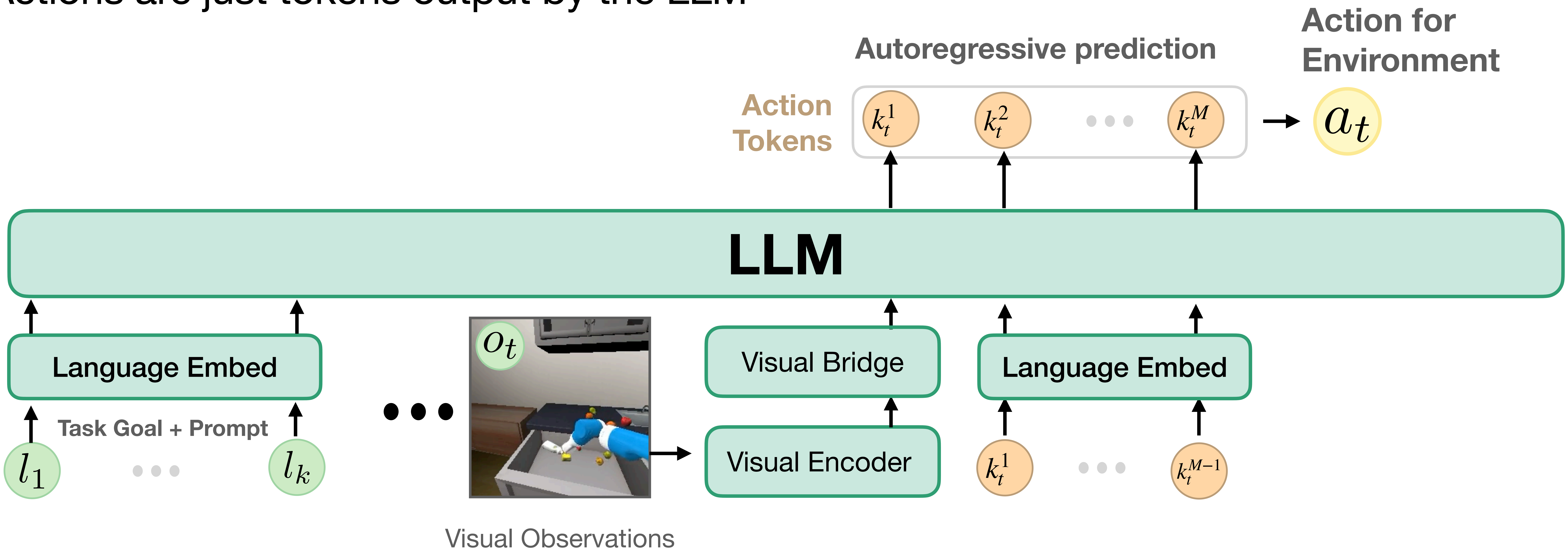
GEA Architecture

Encode visual observations and history of observations for memory



GEA Architecture

Actions are just tokens output by the LLM



But LLMs are trained to output **text**, yet agents require **actions**?

Continuous Low-Level Motor Control

[0.72, 0.24, 0.43, -0.21, …]

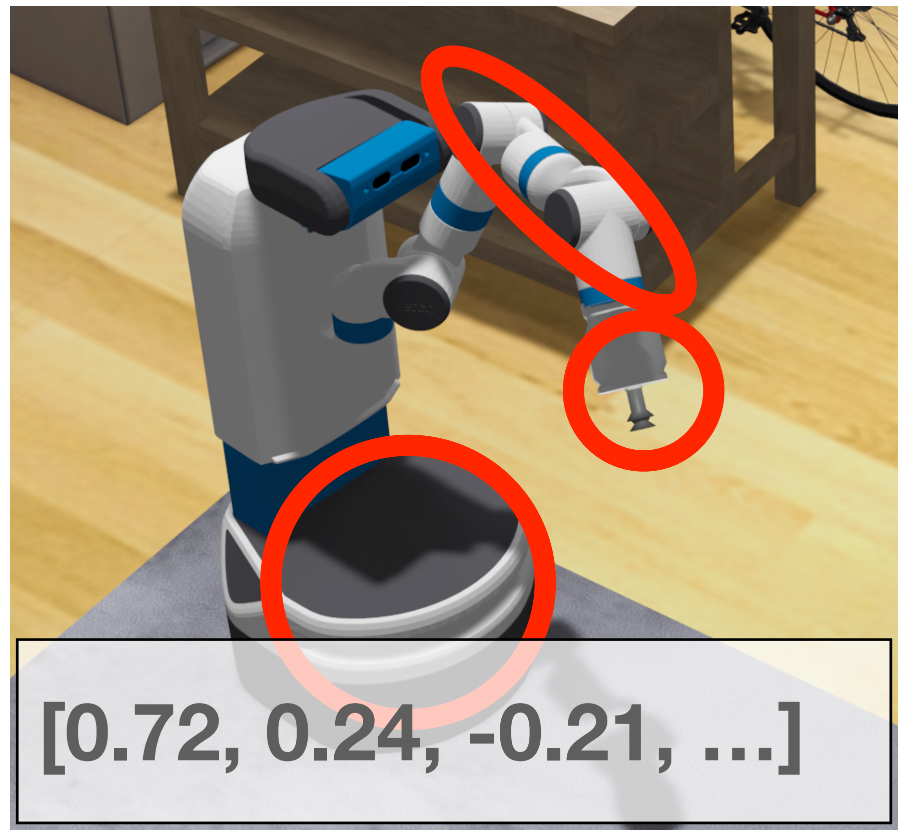
Navigation Control Actions

Turn left
Turn right
Go straight

UI Interaction Actions

Open Safari
Tap 231 492
Search “food near me”
…

GEA Action Tokenization

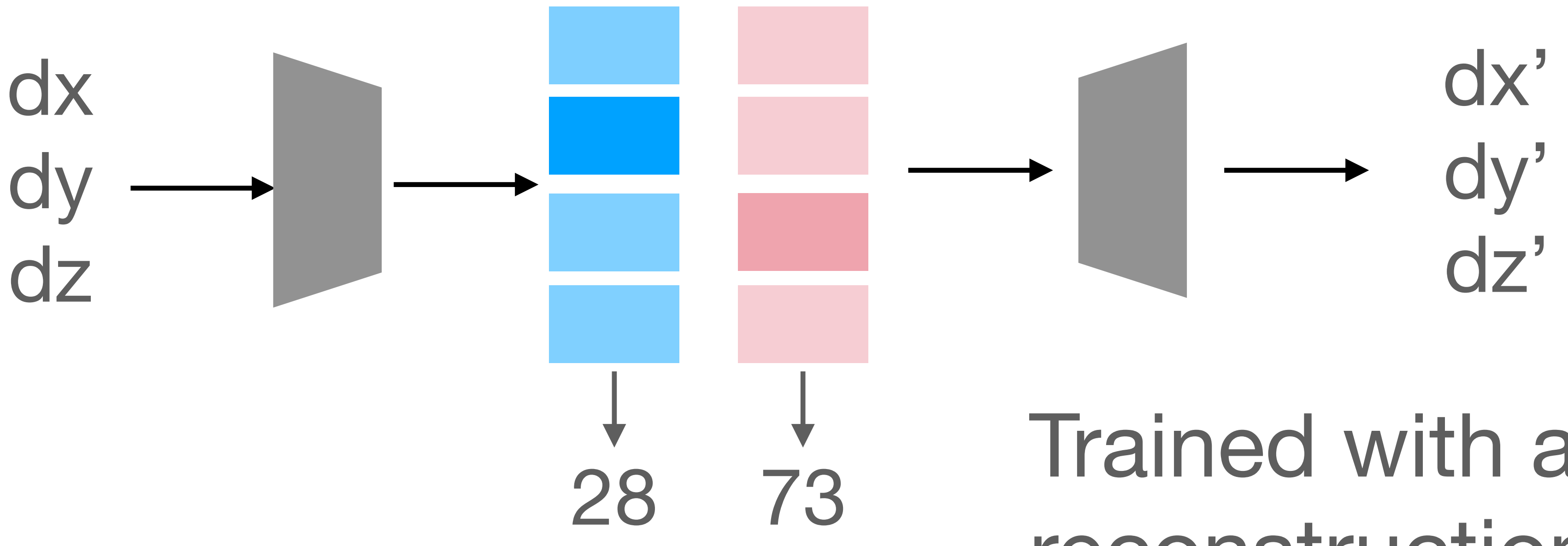


Action is a continuous vector

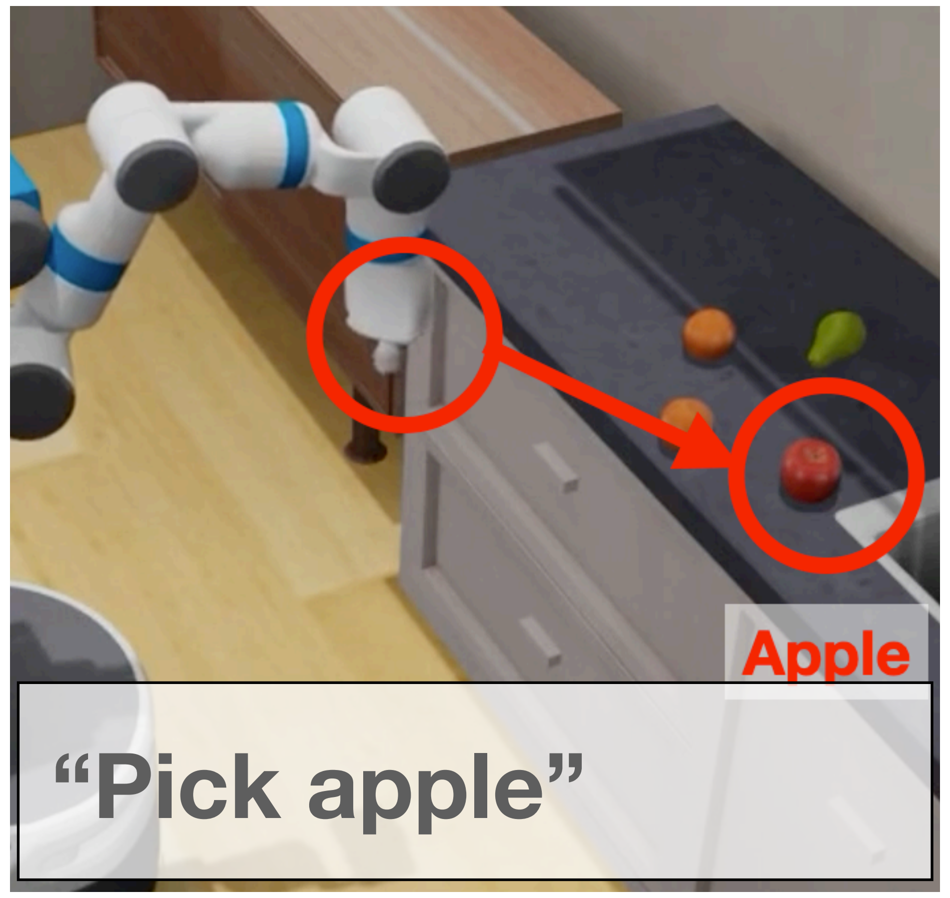
Example: end effector control
[dx, dy, dz]

Learned Tokenization

Residual VQ-VAE for discrete action tokenization



Trained with action reconstruction



Action is a selection from a set of discrete choices

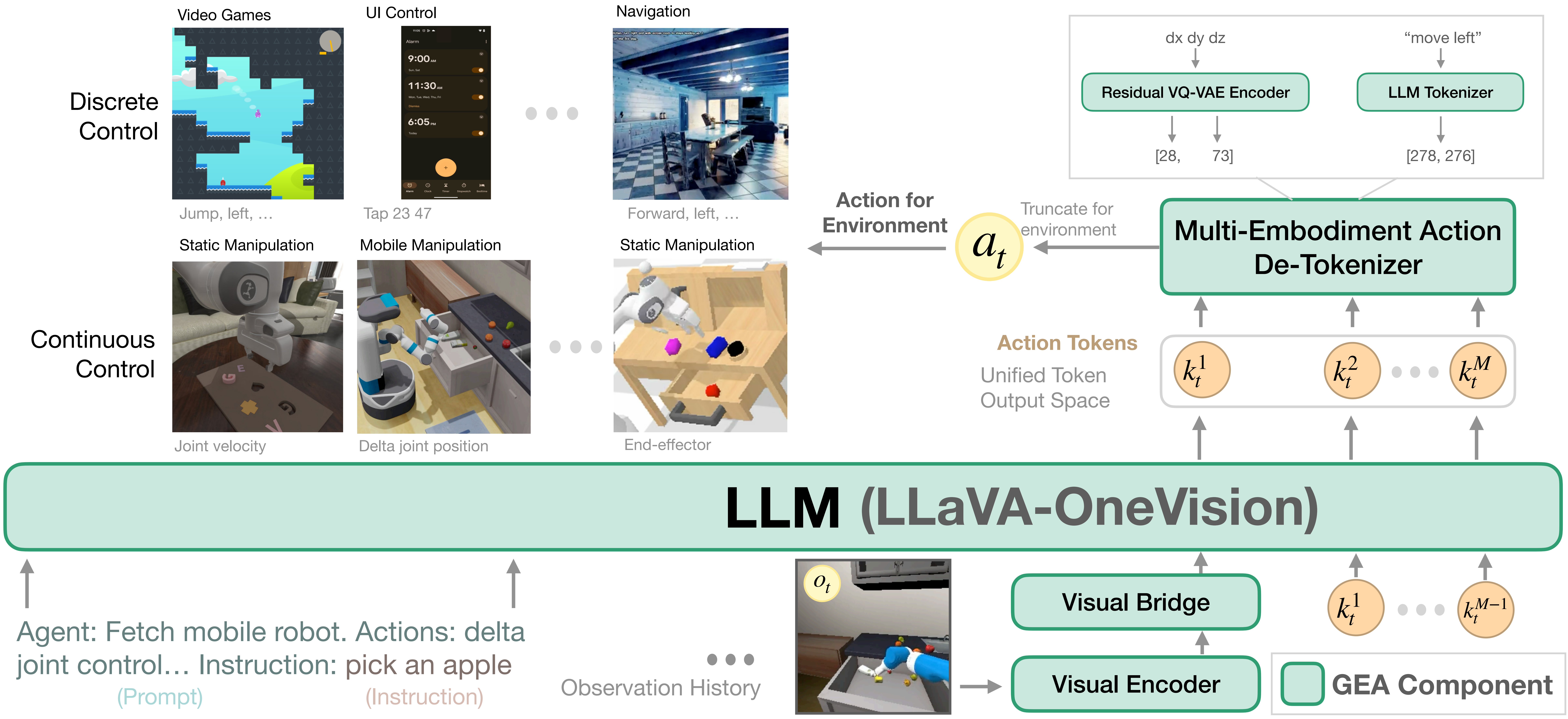
Semantic Tokenization

“pick apple”

↓

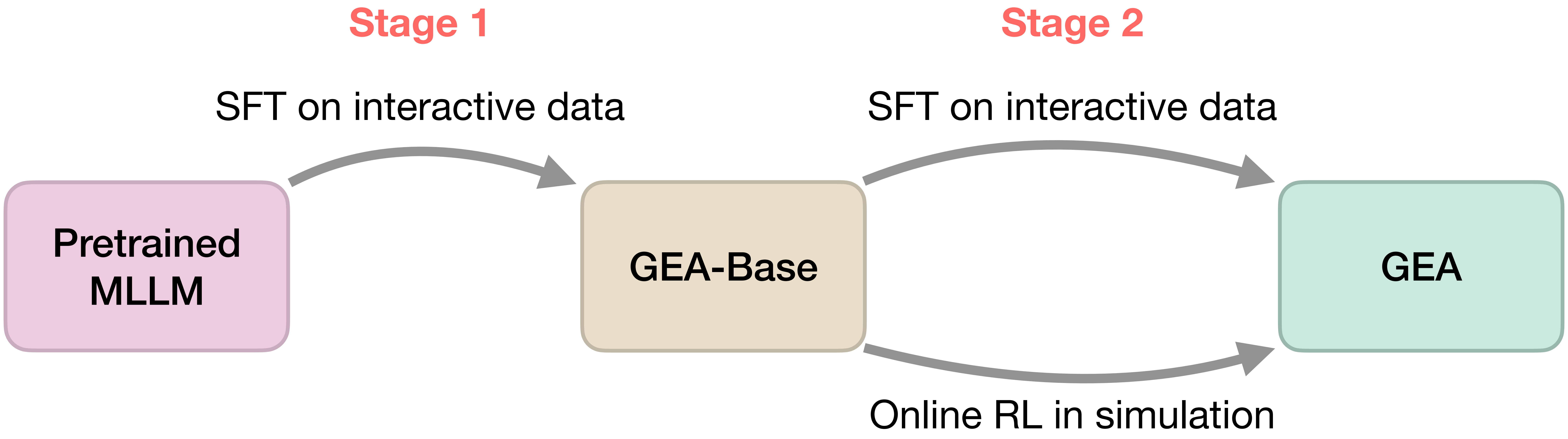
[278,276]

Describe action with language and tokenize with LLM vocabulary



Video Games
UI Control
Navigation
Discrete Control
Jump, left, …
Tap 23 47
Forward, left, …
Static Manipulation
Mobile Manipulation
Static Manipulation
Continuous Control
Joint velocity
Delta joint position
End-effector
dx dy dz
"move left"
Residual VQ-VAE Encoder
LLM Tokenizer
[28, 73]
[278, 276]
Action for Environment
a_t
Truncate for environment
Multi-Embodiment Action De-Tokenizer
Action Tokens
Unified Token Output Space
k_t^1 k_t^2 k_t^M
LLM (LLaVA-OneVision)
o_t
Visual Bridge
Visual Encoder
k_t^1 k_t^{M-1}
GEA Component
Agent: Fetch mobile robot. Actions: delta joint control… Instruction: pick an apple
(Prompt)
(Instruction)
Observation History

Training GEA

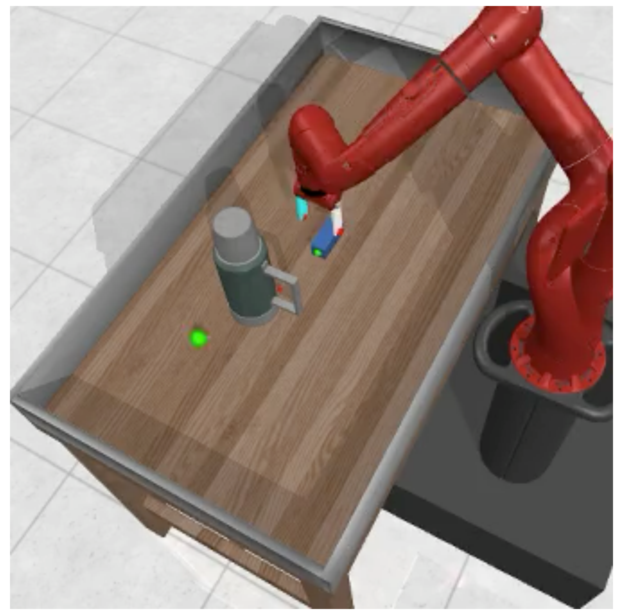


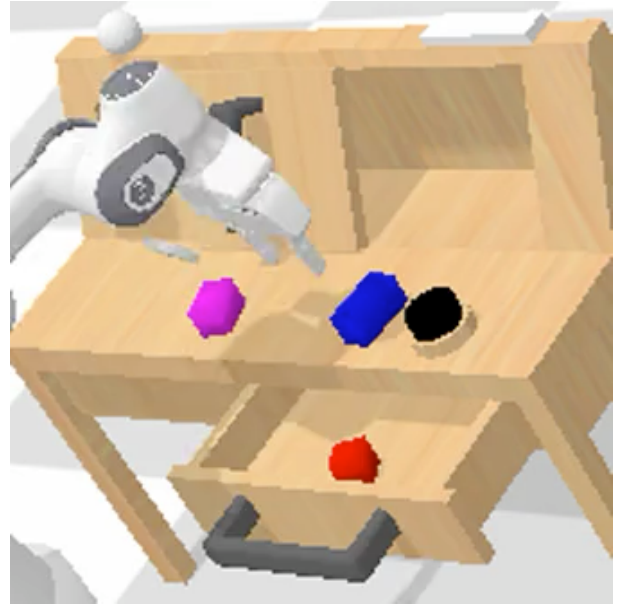
GEA Stage 1: SFT

Collect expert demonstrations in diverse domains for training

From diverse sources, like scripted policies, humans, or RL policies

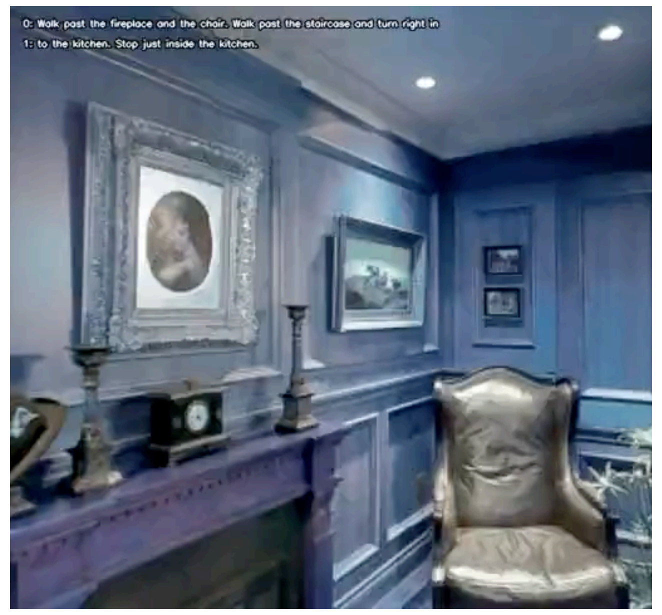
Static Manipulation



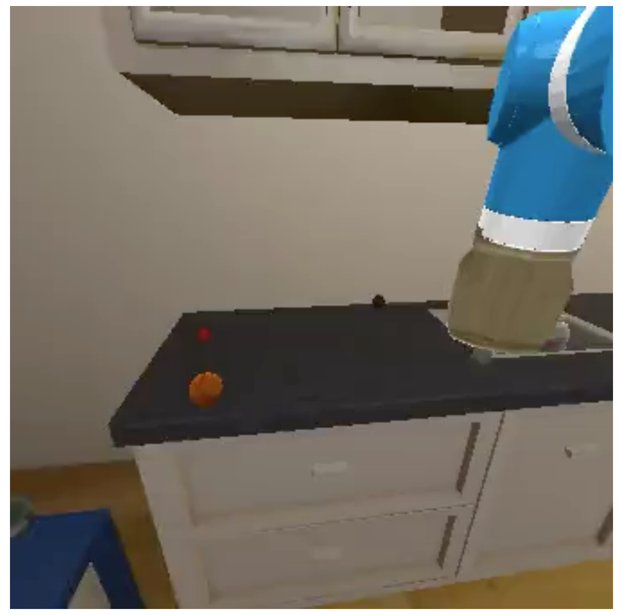


Games

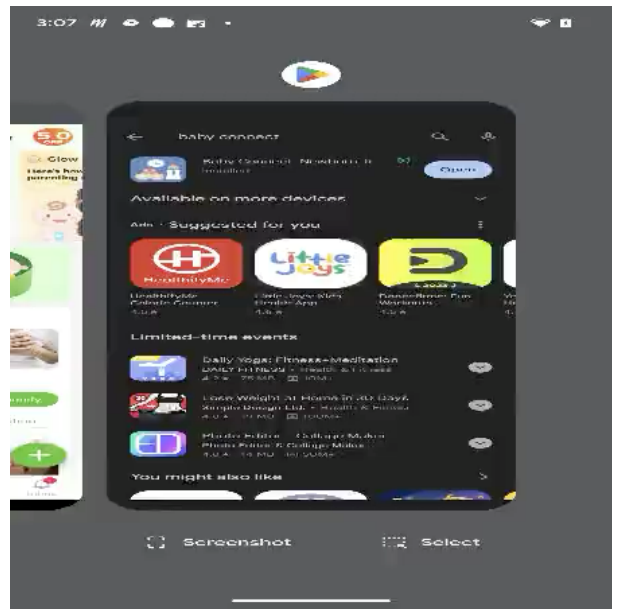
Navigation



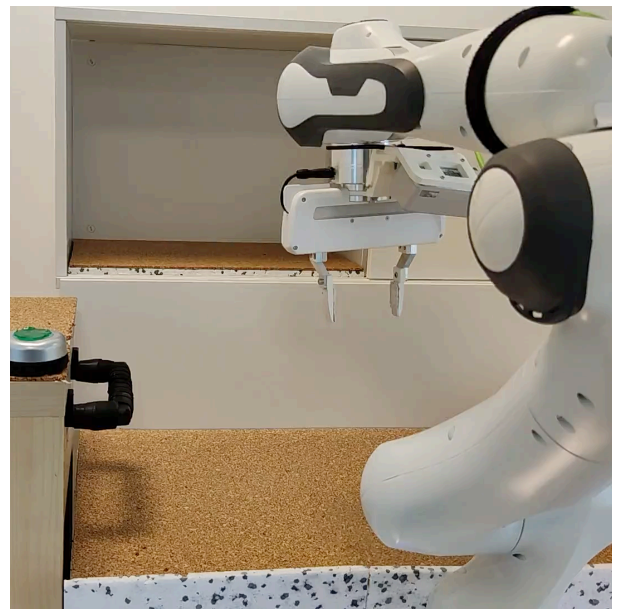
Mobile Manipulation



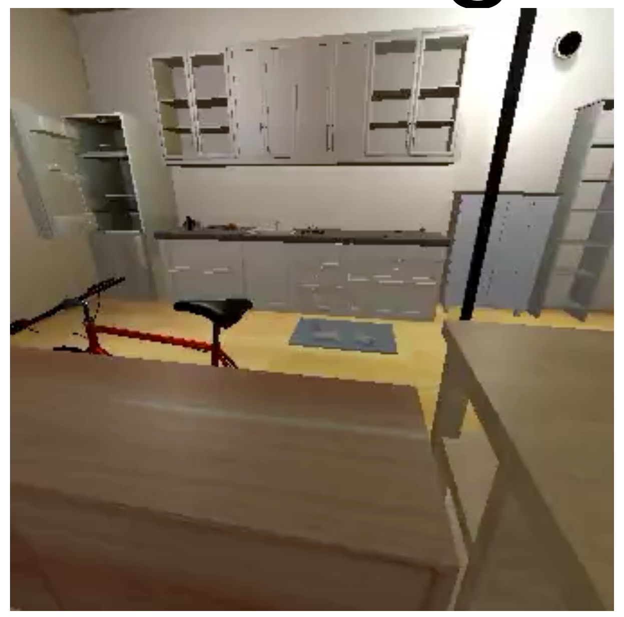
UI Control



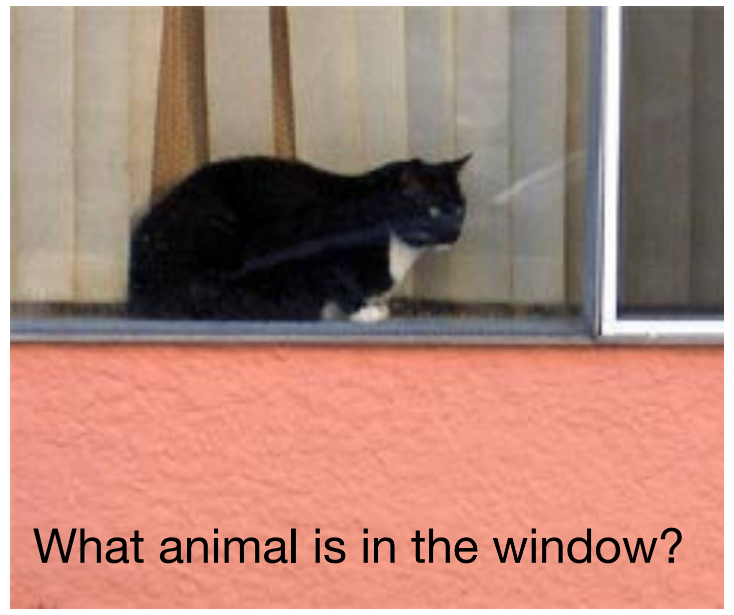
Real Robots



Planning



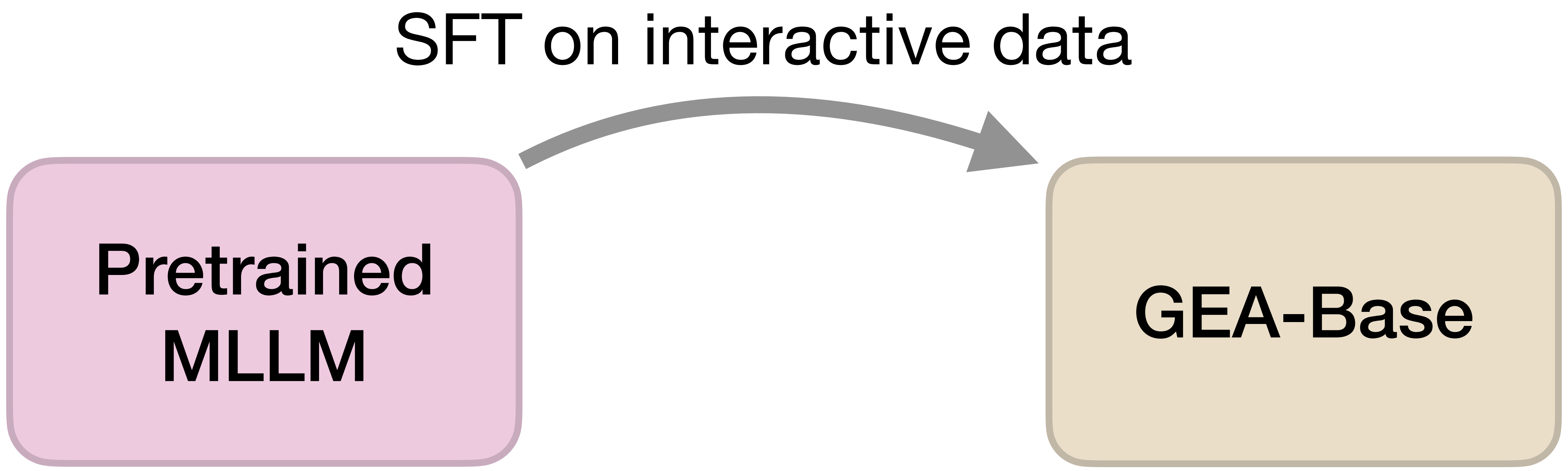
VL Data



GEA Stage 1: SFT

Collect expert demonstrations in diverse domains for training

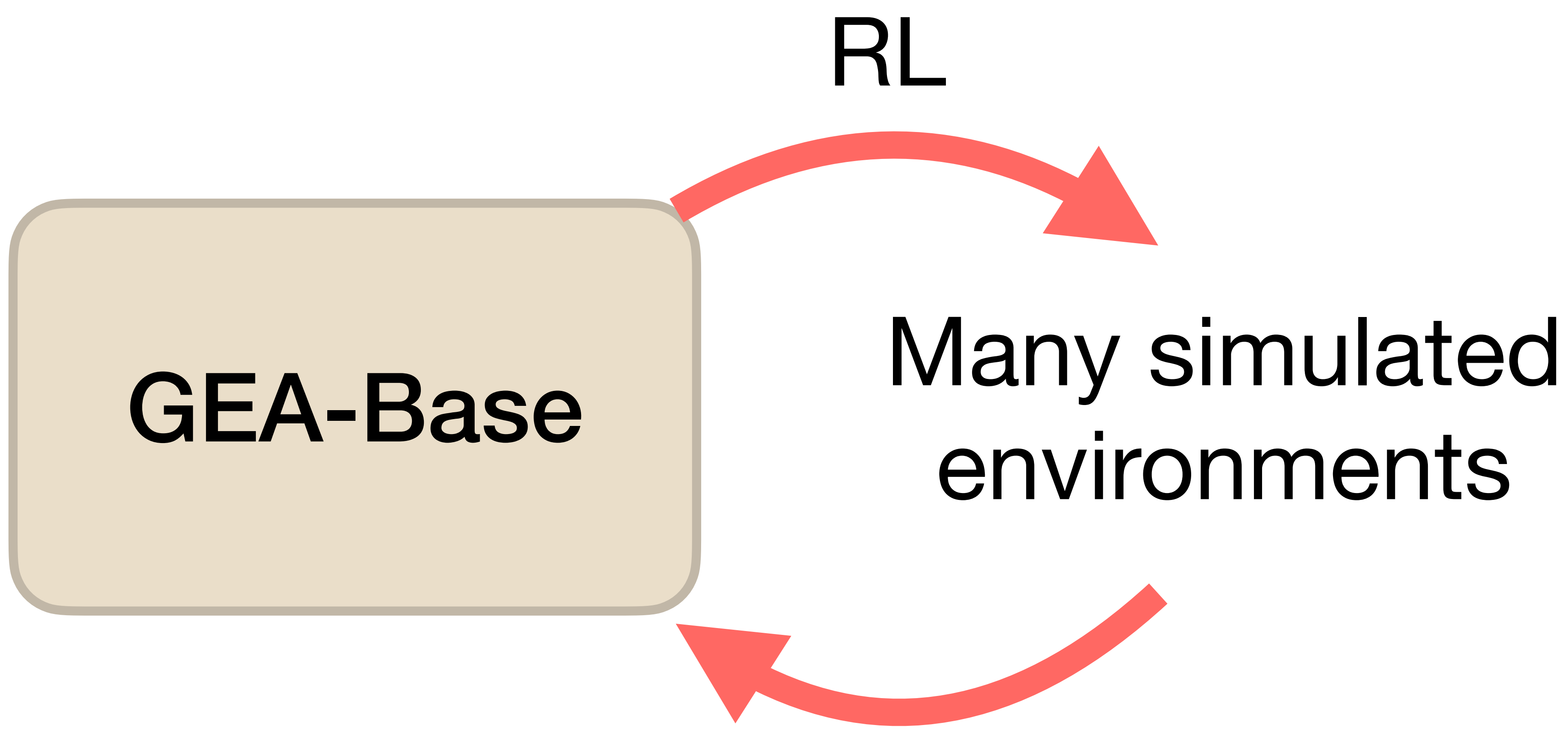
From diverse sources, like scripted policies, humans, or RL policies

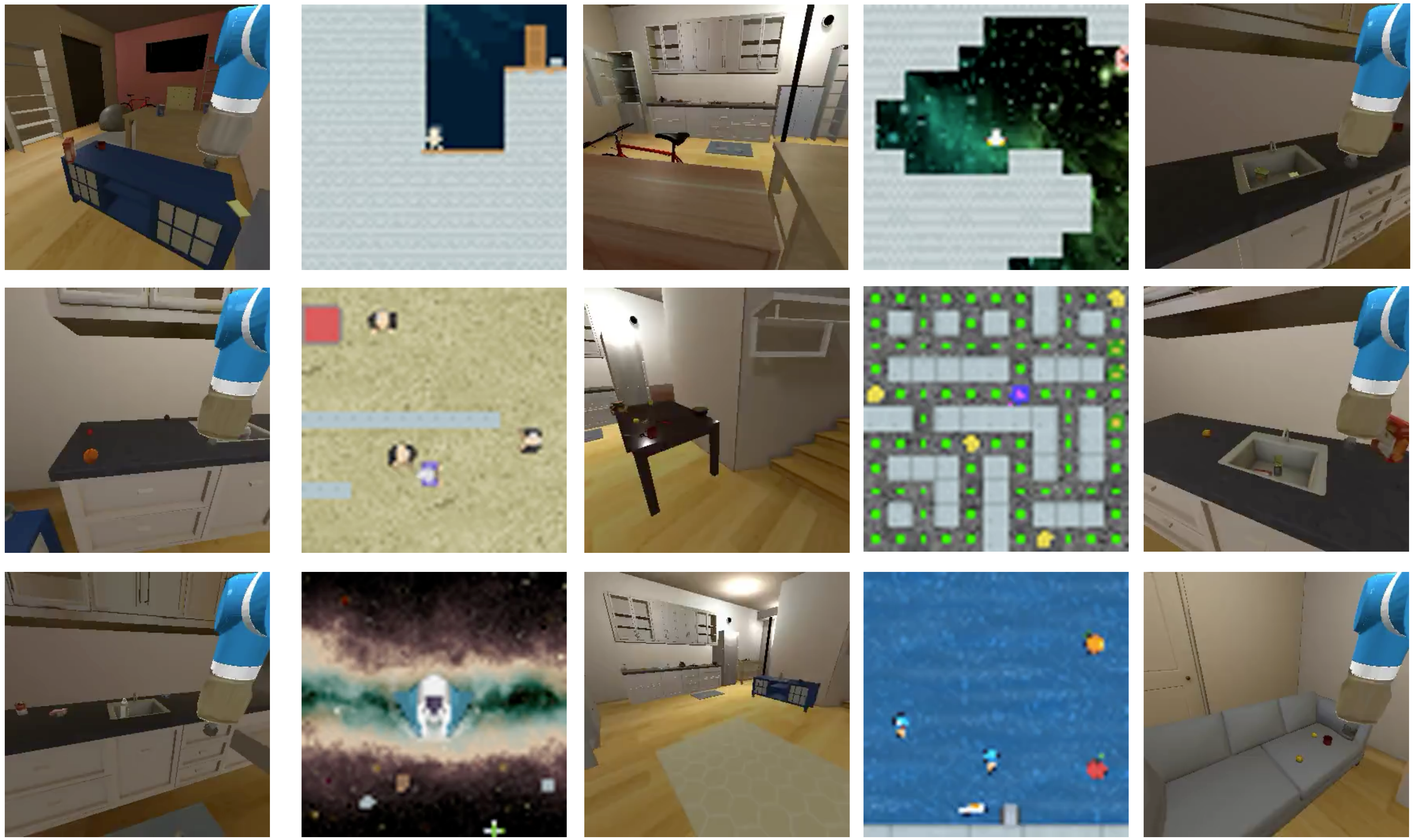


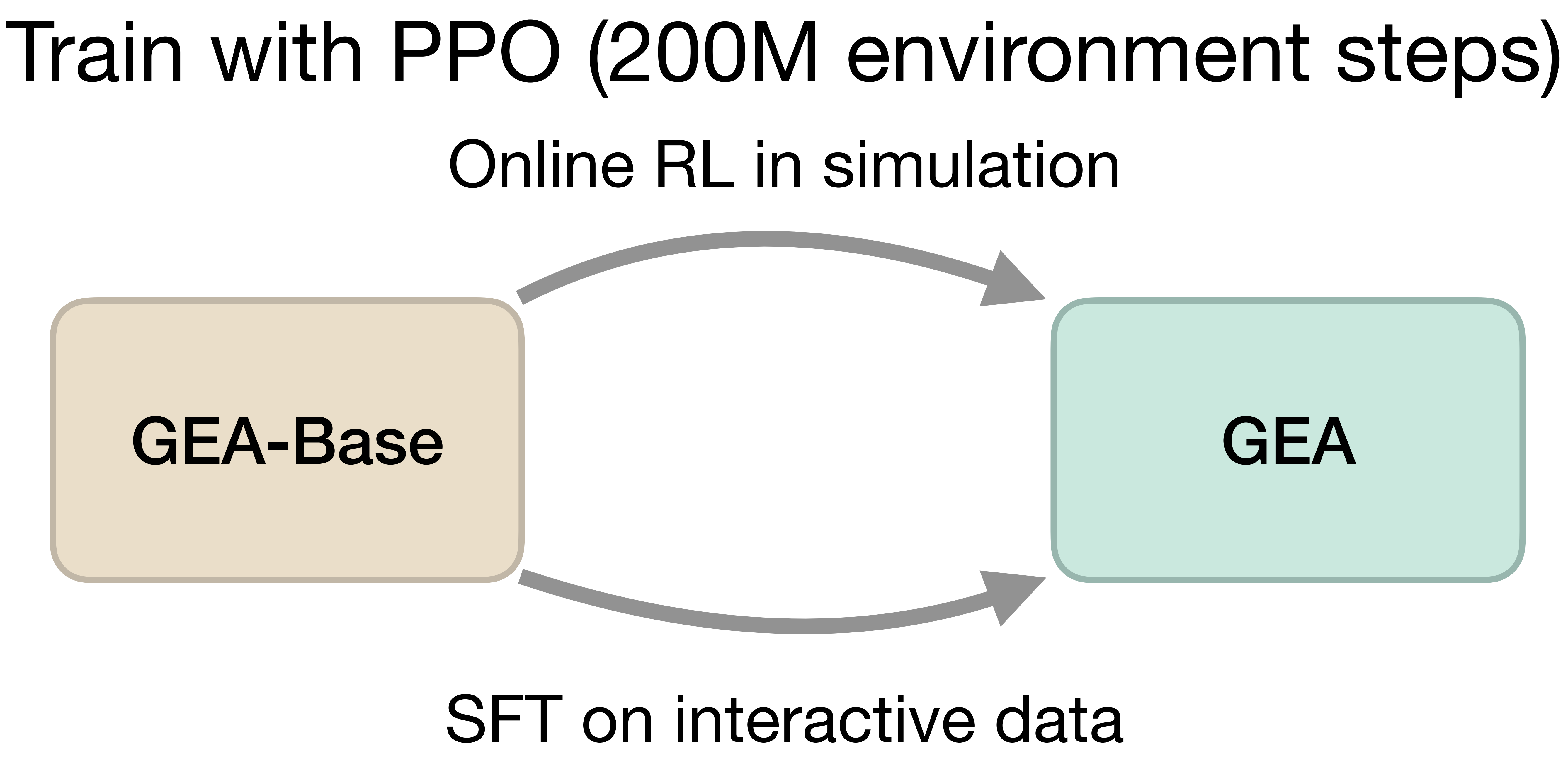
2.2M trajectories, 90 embodiments

GEA Stage 2: RL + SFT

Continue training GEA-Base with RL in interactive tasks






Train with PPO (200M environment steps)
Online RL in simulation
GEA-Base
GEA
SFT on interactive data

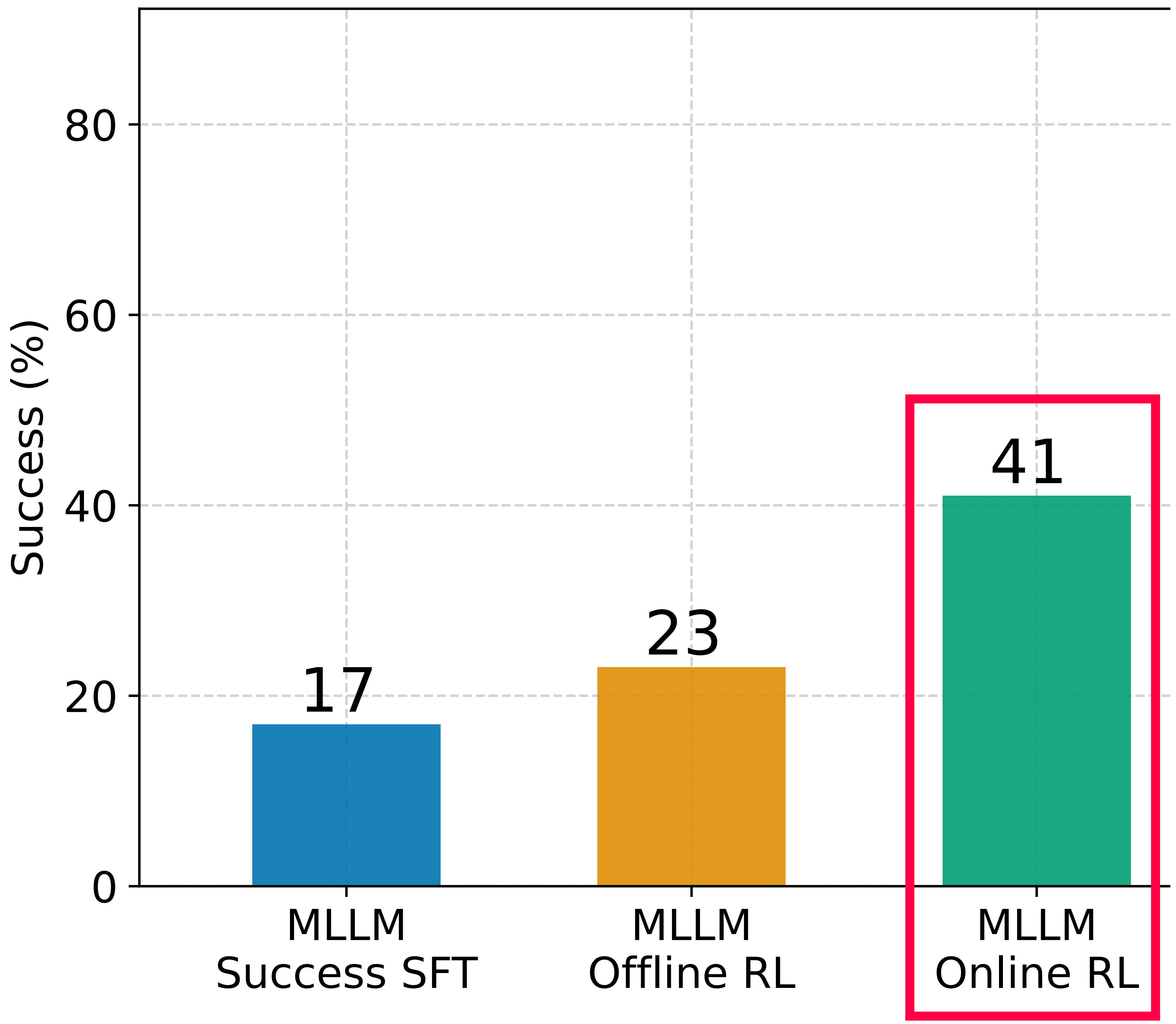
Importance of RL

- **Success SFT**: Collect data from policy, train on only successes
- **Offline RL**: Collect data from policy, train on both success and failure
- **Online RL**: Interact with the current policy in the environment

Importance of RL: A Glimpse of Results

On top of base MLLM (not GEA)

Online RL outperforms SFT and offline RL

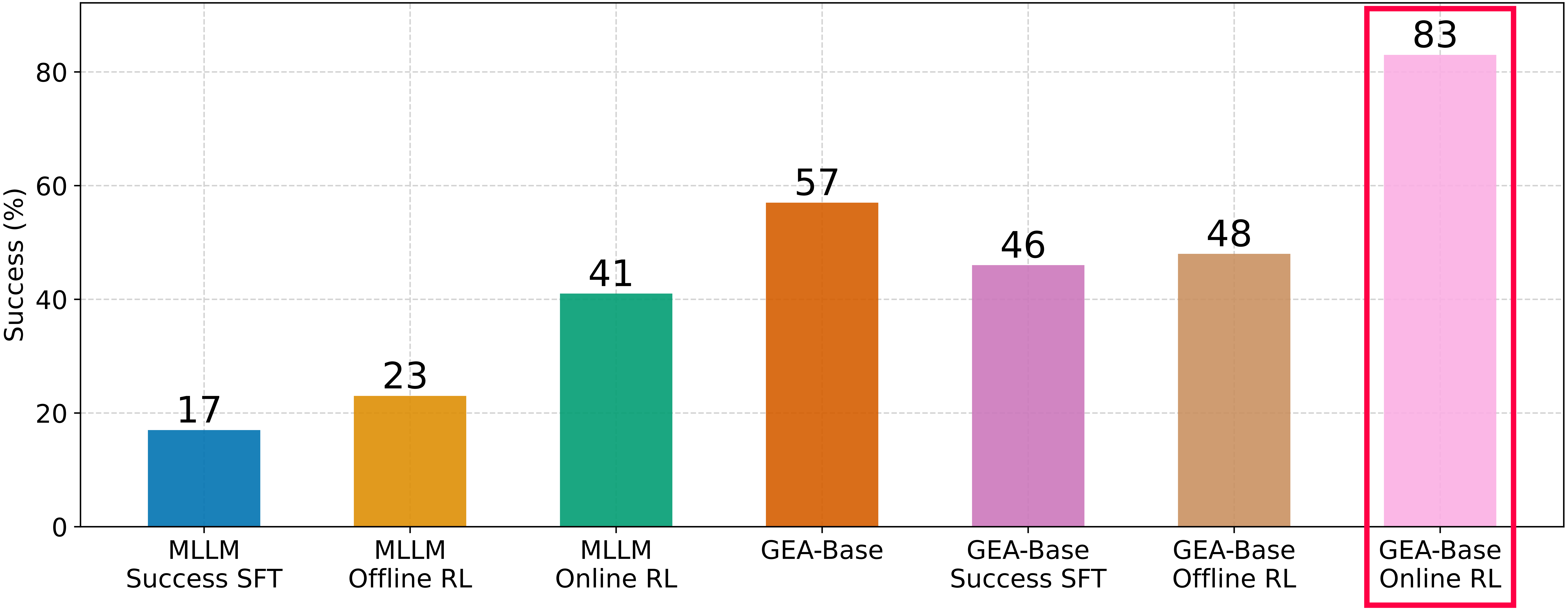


Analysis on a single task (Habitat Pick)

Importance of RL: A Glimpse of Results

Repeat starting from GEA-Base

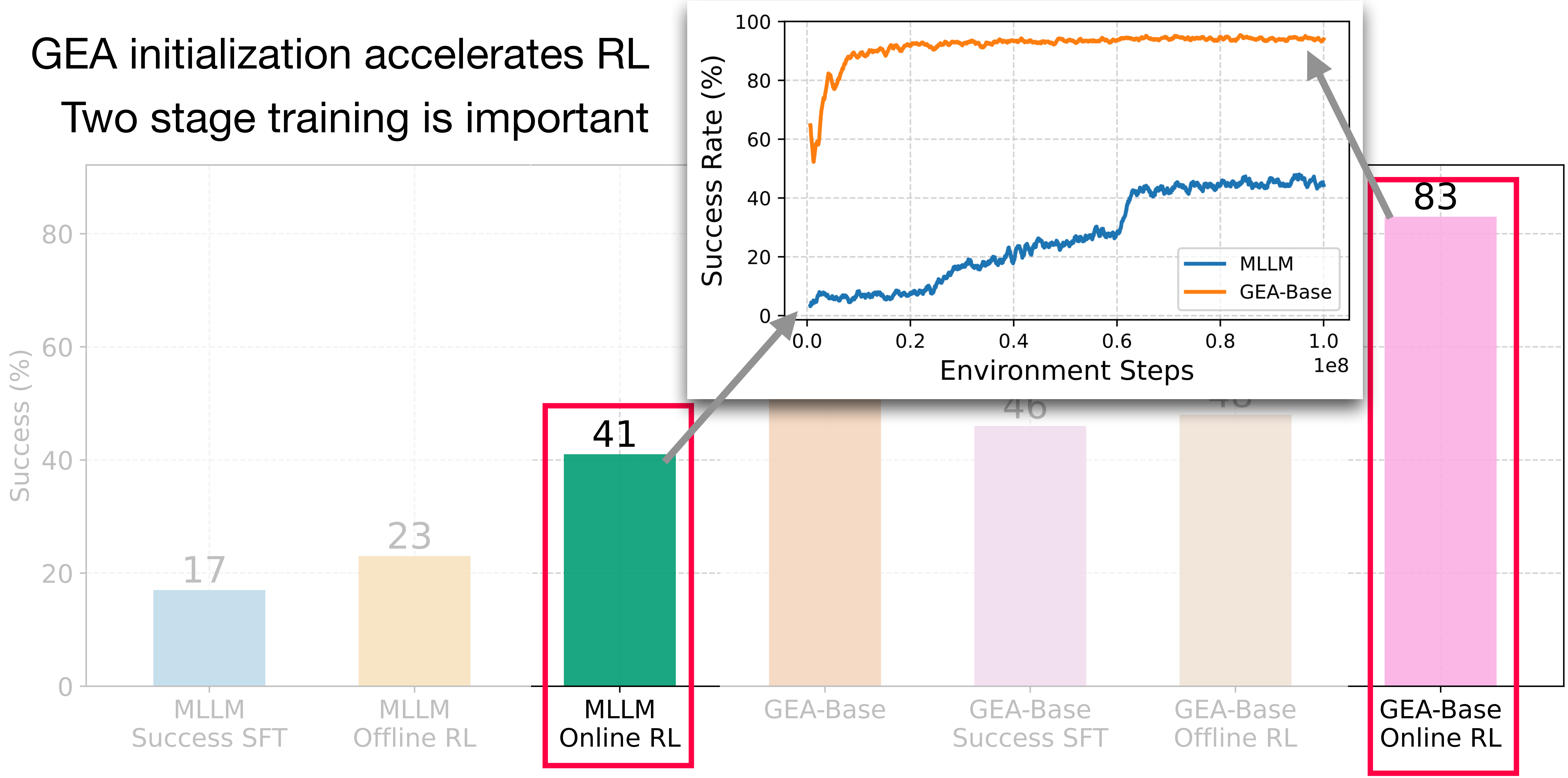
Online RL crucial for GEA



Importance of RL: A Glimpse of Results

GEA initialization accelerates RL

Two stage training is important



Summary

- Image Encoder: Simple method that scales well
  - Using MLLM eval suite as standard protocol for image encoder development
- Multimodal LLM: It’s all about data
- Generalist Agent: RL is the key
- Future directions
  - Unified tokenizer for image understanding and generation
  - Reasoning
  - GUI Agents

Apple Foundation Models

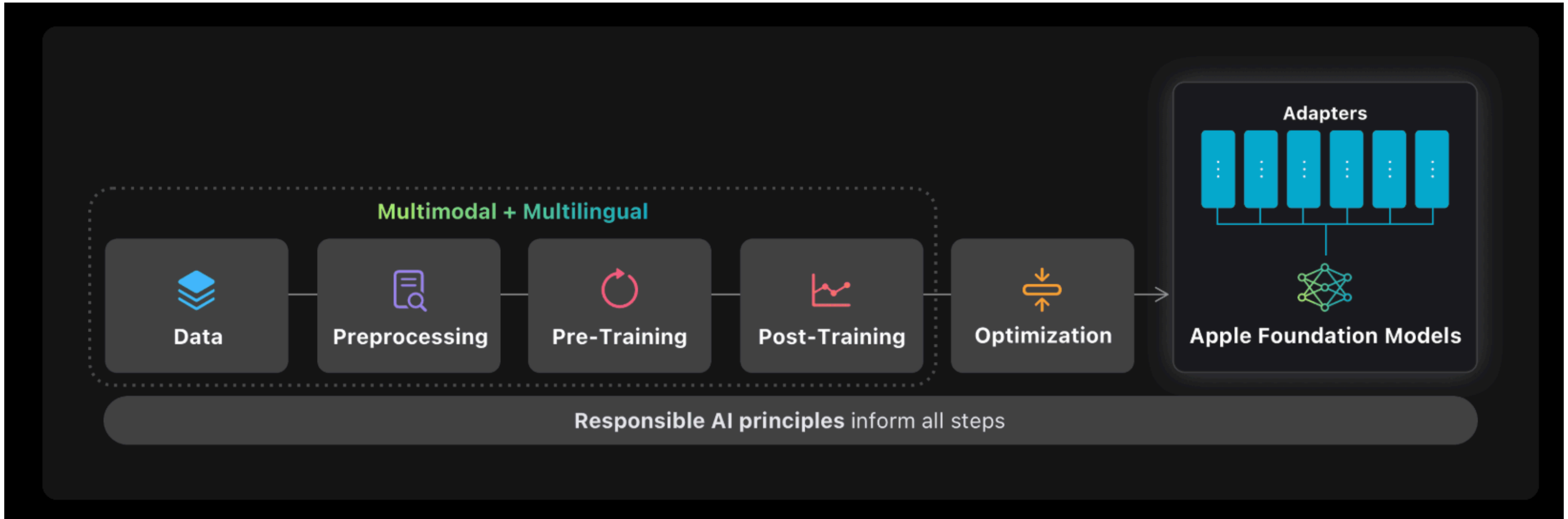


Figure 1: Modeling overview for the Apple foundation models.

https://machinelearning.apple.com/research/apple-foundation-models-2025-updates