



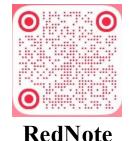


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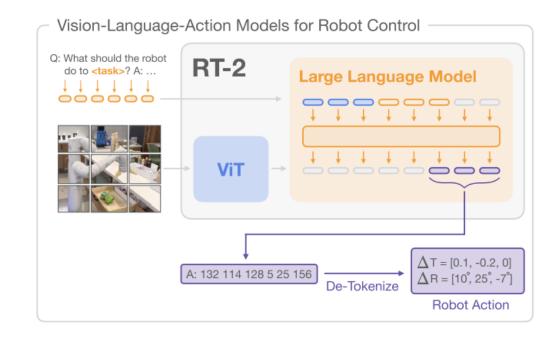
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Part 1.I-Background: From VLM to VLA

- Visual-Language Model (VLM)
 - Integrating visual and language information through cross-modal alignment to achieve scene understanding
- Visual-Language-Action Model (VLA)
 - Vision Language Action Model (VLA) = Vision-Language Model (VLM) + Action Model
 - Integrate vision, language, and action modalities to enable end-to-end learning from perception to decision to execution.
 - They typically fine-tune the pre-trained VLMs to predict robot actions.



Part 1.II-Motivation

Question: Since modern VLA architectures build upon pre-trained vision-language models (VLMs),

1. Can VLAs equipped with the comprehensive capabilities inherent from VLMs?

e.g. Recognizing everyday objects, reasoning about spatial relationships, and solving mathematical problems



User Find the red ball near the gray cat

VLM No, the red ball is not near the gray cat. The gray cat is sitting on a pillow.

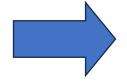
2. Can these capabilities used to enhance generalization?

Part 1.II-Motivation

We argue that a generalizable VLA model

should retain and expand upon the VLM's core competencies:

1. Open-world Embodied Reasoning



The VLA should inherit the knowledge from VLM, i.e., recognize anything that the VLM can recognize, be capable of solving math problems, and possess visual-spatial intelligence

2. Reasoning Following

Effectively translating the open-world reasoning into actionable steps for the robot.

Part 1.II-Motivation

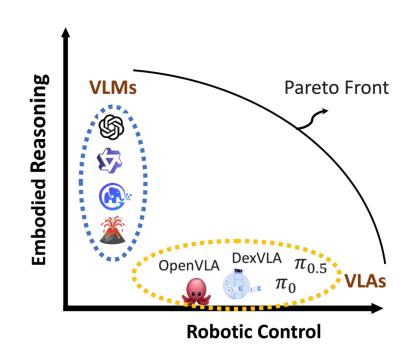
How to enable VLA with

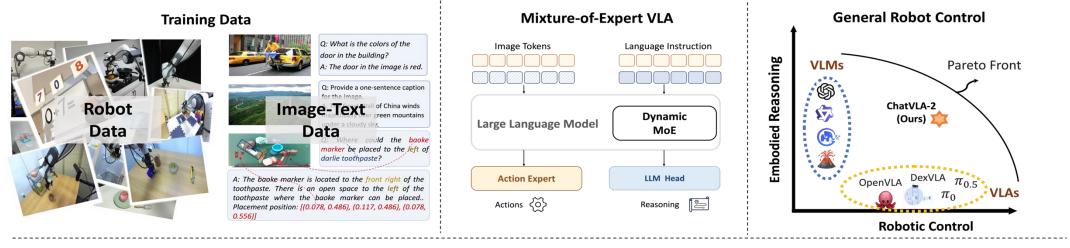
- 1. Open-world Embodied Reasoning
- 2. Reasoning Following considering the large gap between distributions?

We argue that this can be achieved by adhering to two fundamental principles

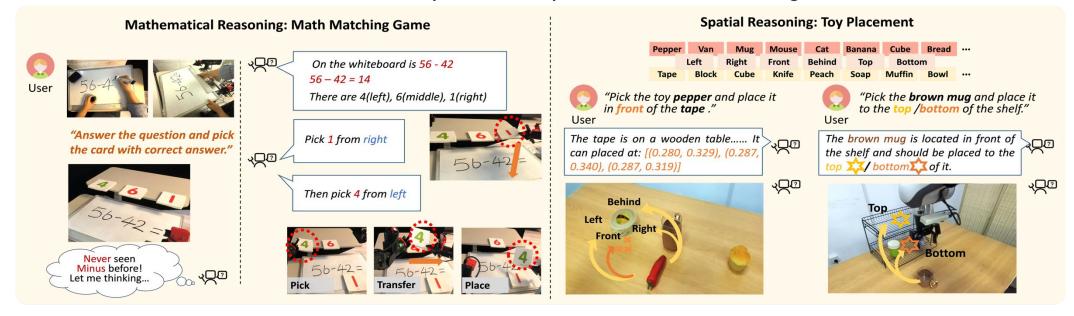
1. Identifying overlapping feature spaces between multimodal understanding and robot control

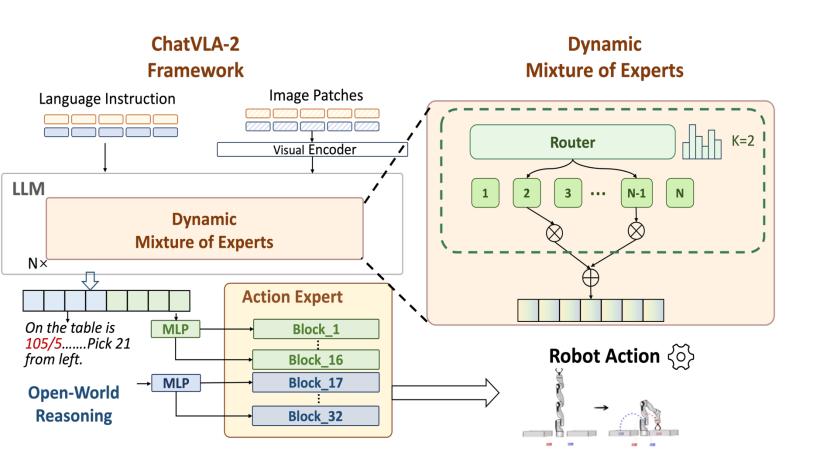
2. Ensuring VLA models act according to their internal reasoning.





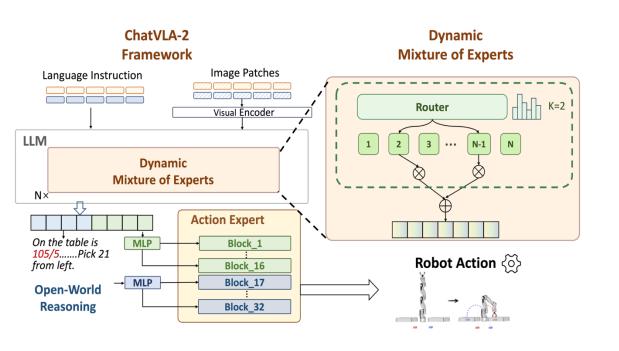
Robot Manipulation with Open-World Embodied Reasoning





Model Architecture

A dynamic mixture-of-experts architecture to disentangle conflicting features between multimodal understanding and robotic control, while effectively integrating mutually beneficial features.



Model Architecture

 A reasoning-following enhancement module is incorporated to ensure that the VLA model adheres to logical reasoning when performing actions.

Original ScaleDP AdaLN:

$$AdaLN_i(x) = (\gamma_i(t, o) + 1) x + \beta_i(t, o), \quad 1 \le i \le N.$$



ChatVLA-2 AdaLN (piecewise over depth):

AdaLN_i(x) =
$$(\gamma_i(t, o) + 1) x + \beta_i(t, o)$$
 if $i < \frac{\hbar}{2}$

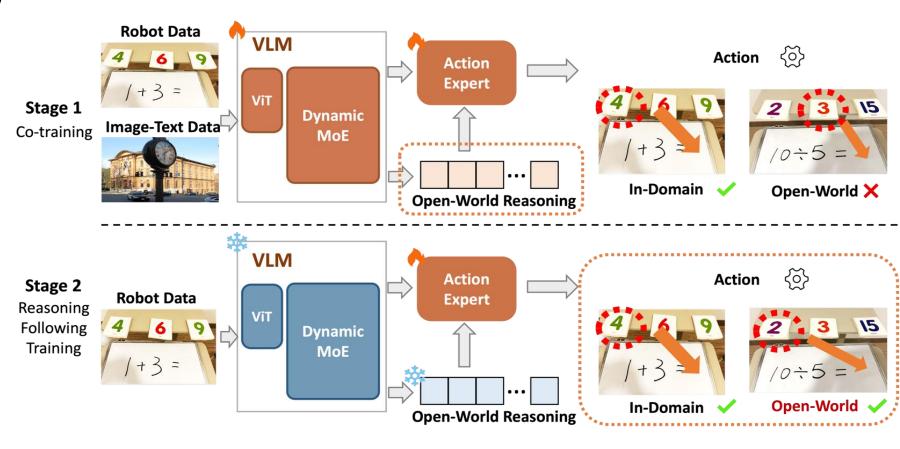
AdaLN_i(x) =
$$(\gamma_i(t, r) + 1)x + \beta_i(t, r)$$
 if $i \ge \frac{N}{2}$

where the original observation o is replaced to reasoning r in the latter half layers.

Two-Stage Training Strategy

Stage 1

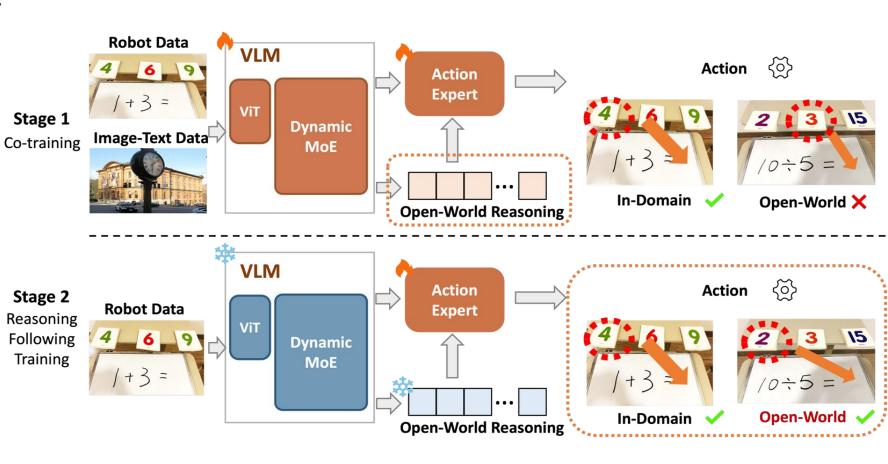
Co-training on image-text and robot data is essential for enabling the robot foundation model to reason and understand scenes in the wild. During this stage, we train the model on both tasks.



Two-Stage Training Strategy

Stage 2

We freeze the entire VLM and train only the action expert, thereby preserving open-world reasoning while enhancing instruction-following abilities in VLA.



Part 3.I- Experimental setup

Franka Setup



Camera

Math Matching Game Answer the question and pick the card with correct answer. Instruction:

Step

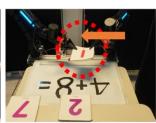
To



On the board is 18+16=34... Pick 34 from right

Steps



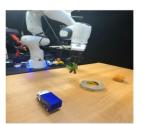


On the board is 4+8, 4+8=12..... There are 1(left), 2(middle), 7(right) First, pick 1 from left

Then pick 2 from middle

Toy Placement

Instruction: Pick the [obj] and place it to [place] of the [target]



Pick the avocado Pick the corn





Pick the mug



Behind the tape



Left of pink block



Right of orange bus



Front of bowl



Top/Bottom of shelf

Part 3.I- Results on Mathematical Reasoning

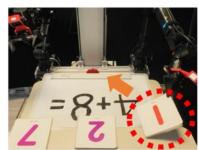
Mathematical Reasoning: Math Matching Game

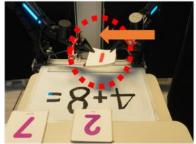
Instruction: Answer the question and pick the card with correct answer.

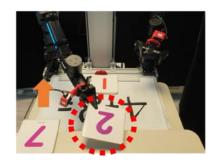
1 Step



2 Steps







On the board is 18+16=34... Pick 34 from right On the board is 4+8, 4+8=12......
There are 1(left), 2(middle), 7(right)
First, pick 1 from left

Then pick 2 from middle

Evaluation metrics

- 1) Manipulation success rate
- 2) OCR

recognizing hand-written numbers: 1' identifying card values and their positions: 1' correctly recognizing the sign: 2'

3) Mathematical reasoning

correct answer: 1'

correctly selecting the card: 1'

Part 3.1- Results on Mathematical Reasoning

Table 1: **Results on the math matching game.** We evaluate multiple models on both in-domain settings, where the data is presented in the training data, and open-world setups. We evaluate average score of **OCR** (4 scores in total) and mathematical reasoning (2 scores in total), and average success rate of task execution at both setups.

Method	In Domain Reasoning Score Success Rate		Open-World OCR Score Math Reasoning Score Success Rate			
Octo [70]	/	2/13	/	/	0/52	
Diffusion Policy [32]	/	7/13	/	/	3/52	
OpenVLA [31]	/	2/13	/	/	0/52	
GR00T N1 [66]	/	4/13	/	/	3/52	
DexVLA [2]	5.2/6	12/13	0.21/4	0.06/2	10/52	
ChatVLA [7]	5.8/6	10/13	1.08/4	0.42/2	4/52	
π_0 [1]	/	12/13	/	/	8/52	
ChatVLA-2 (Ours)	6.0/6	11/13	3.58/4	1.73/2	43/52	

Part 3.II- Experimental setup

Spatial Reasoning: Toy Placement

Instruction: Pick the [obj] and place it to [place] of the [target]







Pick the mug

To



Behind the tape



Left of pink block



Right of orange bus



Top/Bottom of Front of shelf bowl

...

Evaluation metrics

Pick the avocado Pick the corn

- 1) Manipulation success rate
- 2) Object recognition score
- 3) Spatial affordance score

Table 2: **Results on the toy placement task.** We evaluate multiple models on both in-domain settings, where the data is presented in the training data, and open-world setups. We evaluate average object recognition score, spatial affordance score and task success rate at both setups.

Method	od In Domain			Open-World			
Manipulation	Object recognition	Spatial Affordance	Avg. Success Rate	Object recognition	Spatial Affordance	Avg. Success Rate	
Octo [70]	/	/	19/67	/	/	13/156	
Diffusion Policy [32]	/	/	52/67	/	/	17/156	
OpenVLA [10]	/	/	23/67	/	/	10/156	
GR00T N1 [66]	/	/	31/67	/	/	12/156	
DexVLA [2]	1	0.97	63/67	0.23	0.12	36/156	
ChatVLA 7	1	0.97	60/67	0.71	0.35	22/156	
π_0 [1]	/	/	61/67	/	/	25/156	
ChatVLA-2 (Ours)	1	0.99	61/67	0.94	0.88	127/156	

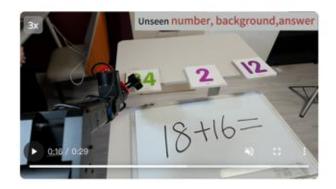
Part 4 - Demos

Solving Sequential Tasks



Unseen number, answer, background, and even symbol!





More on website!

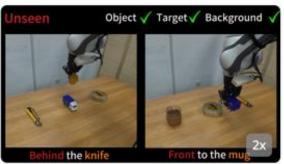
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Part 4 - Demos

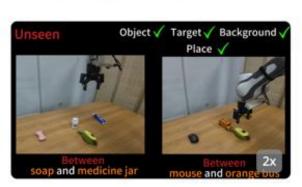


Object √ Target √ Background √

to the kn

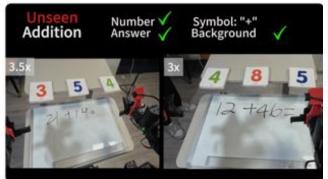


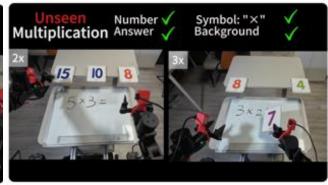


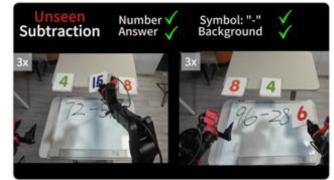


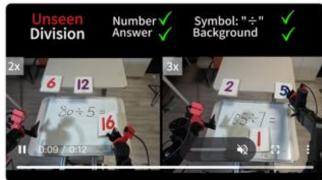
to the kni











More on website!

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Thanks

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