模式分析与机器智能
工业和信息化部重点实验室
MIIT Key Laboratory of
Pattern Analysis & Machine Intelligence

ParNeC 模式识别与神经计算研究组
PAttern Recognition and NEural Computing

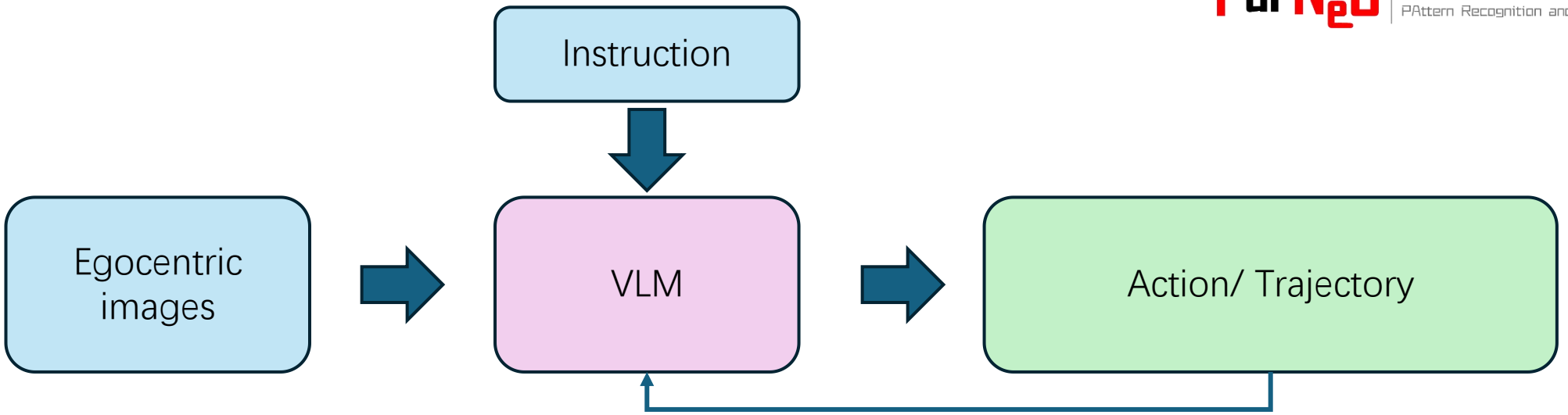
Recent Advances in Vision-and- Language Navigation

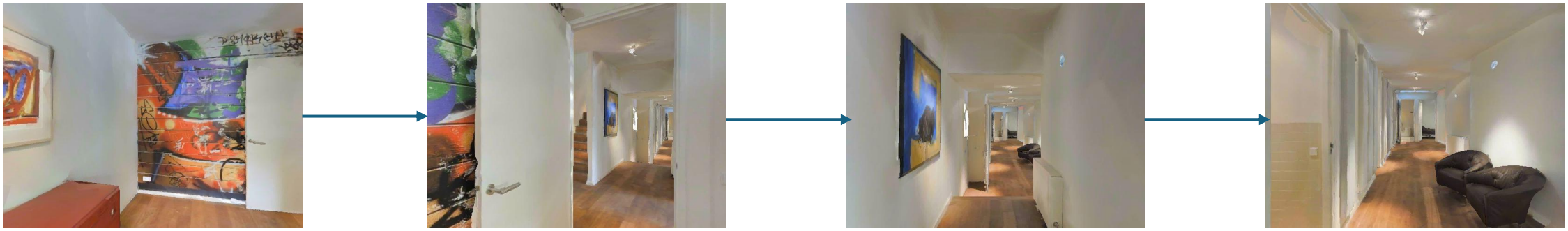
欣子豪

2026. 4. 20

Contents

VLN





Now you are facing towards the wall, slightly turn to your right, you can see a open door to your right, exit room through an open door and move forward, there is a wall art to the left side of the wall and few steps in-front of you, walk down the steps and move forward, there are two black couches to your right, that's your end point.

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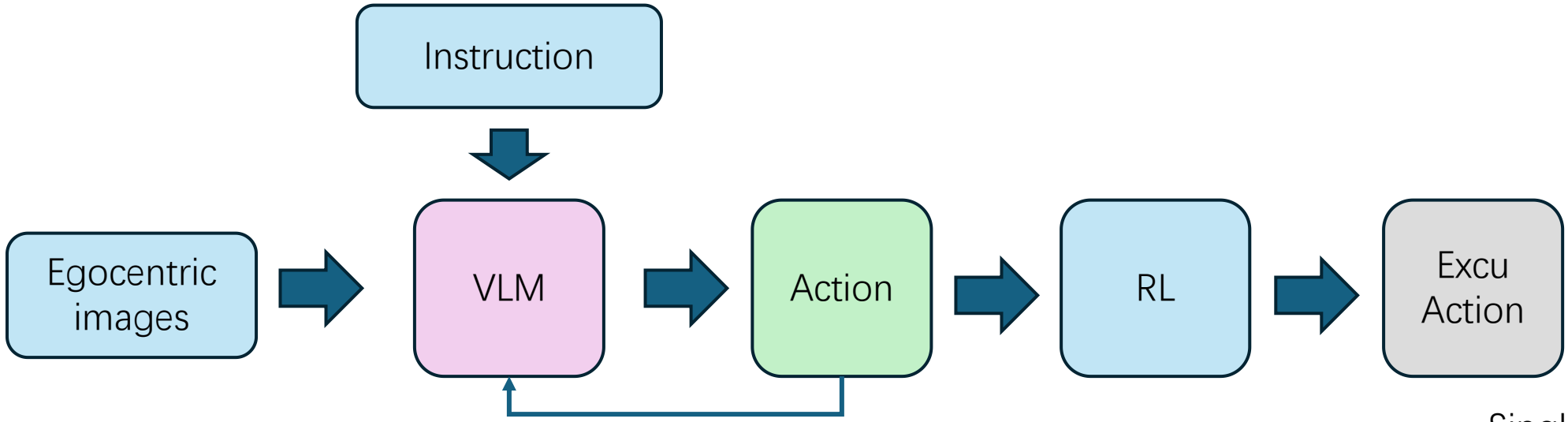
What does VLM need to learn?

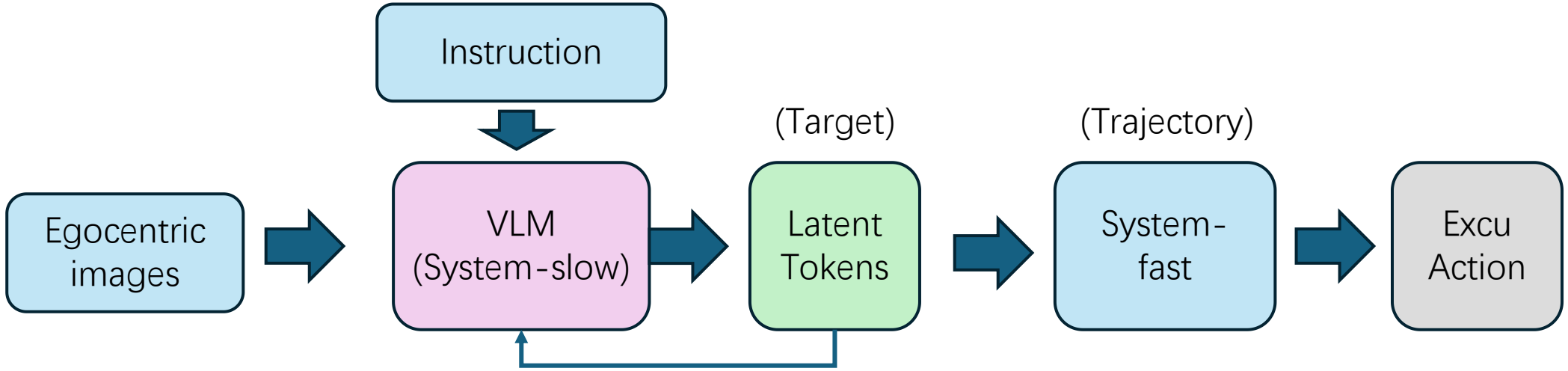
1. Depth estimation: How far is the wall/door?
2. Contextual semantic analysis: What exactly does "slightly" refer to in terms of perspective?
3. Long and short memory
4. Action Space

…

VLN

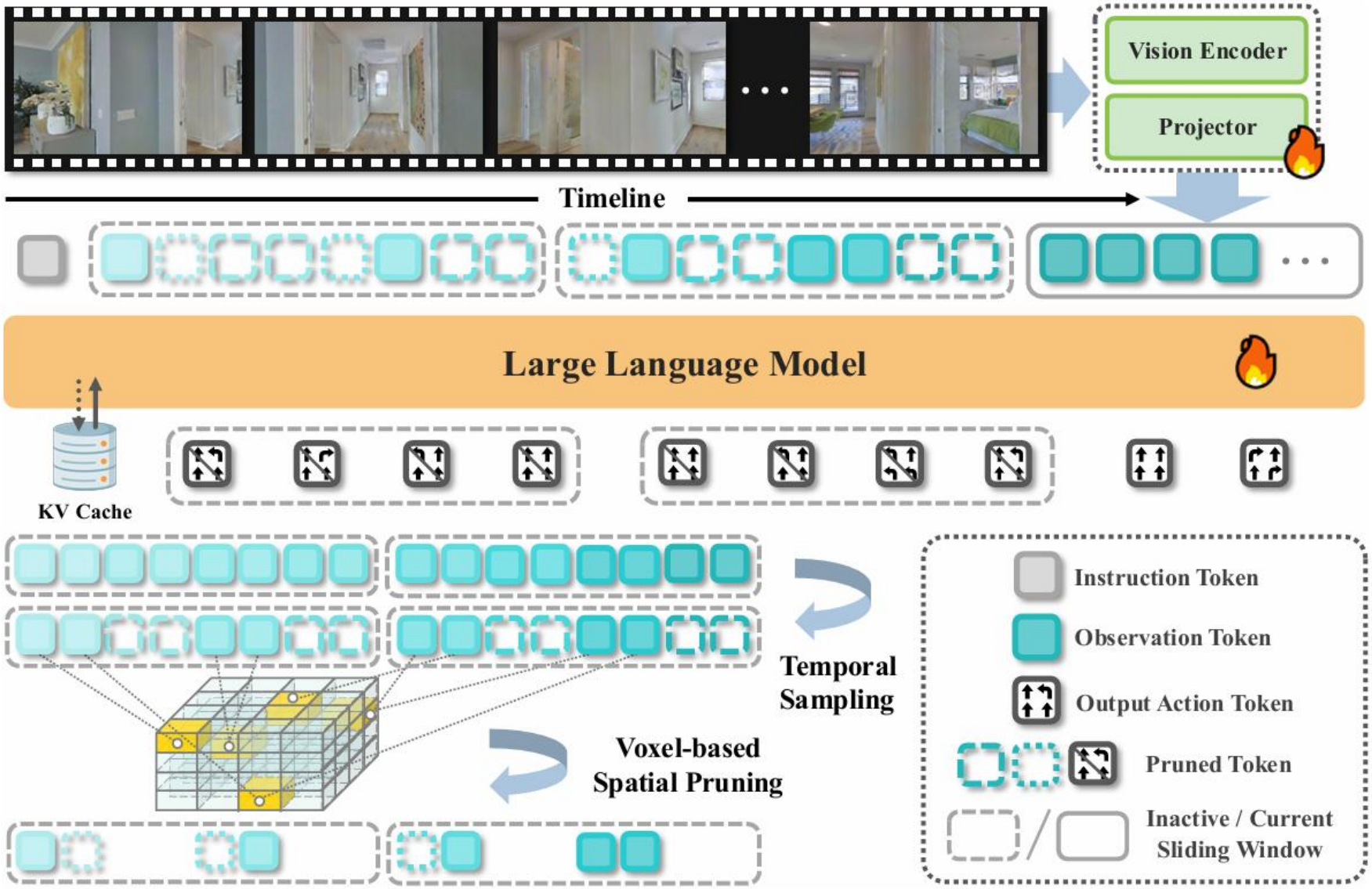


Single-System



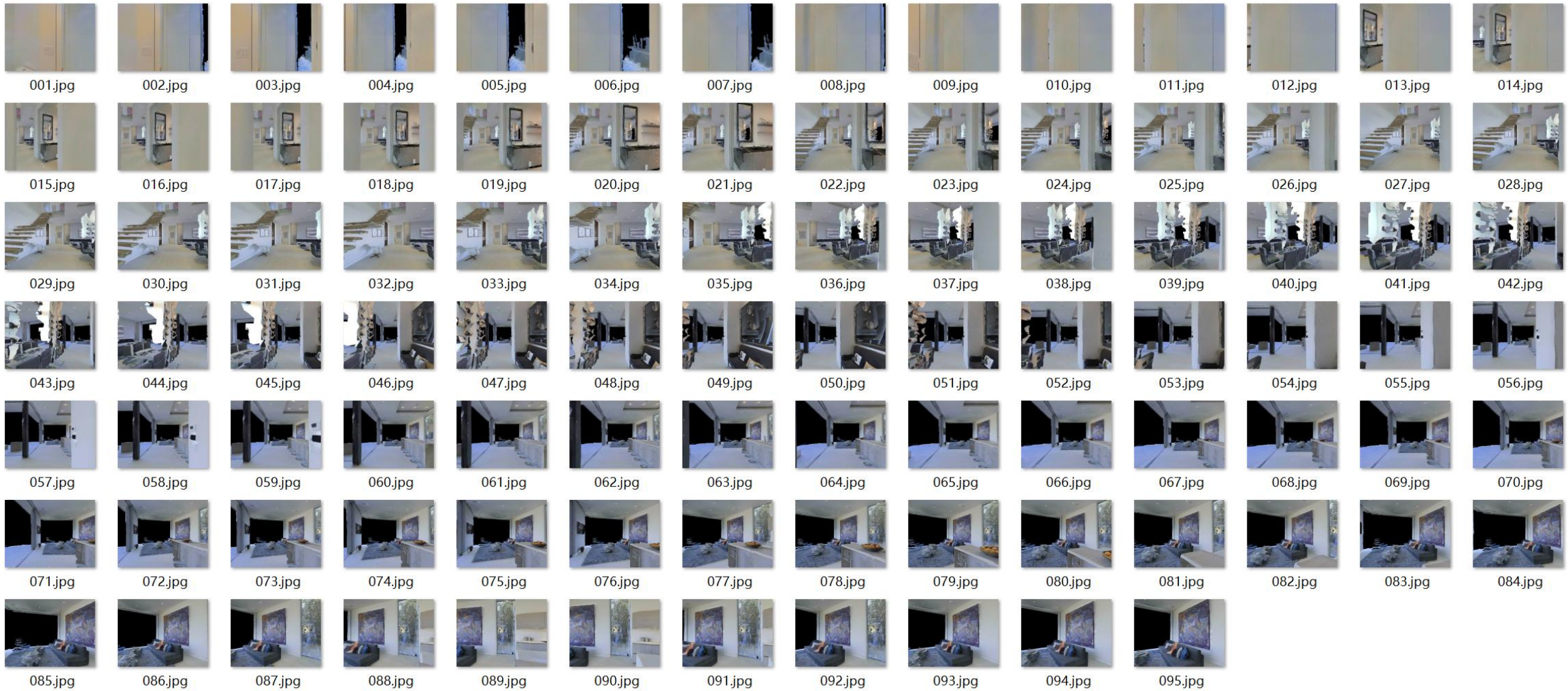
Dual-System

StreamVLN（Single-System, ICRA2026）



1. Long and short term memory
2. Positioning and planning navigation capability
3. Exploration and error correction

VLN – Long Term Memory



~15m path = ~100 ego-centric frames

StreamVLN（Single-System, ICRA2026）

1. Uniform Sampling
2. Voxel-based Cutting

Memory:

8 history frames

+

4 current frames

~4k tokens

Qwen2.5-VL-7B (BF16)

Vision Tower: 640 * 480 image = 46 * 34 patch = 1564 tokens

LLM (after merge): 640 * 480 image = 23 * 17 patch = 391 tokens

KV Cache = ~23 MB

Peak Inference Mem = Model Weight + Vision Tower Peak
+ LLM Prefill Peak + KV Cache + Allocator Reserve

↓

Hidden + QKV + MLP ≈ 100-300 MB / frame

VLN – Long Term Memory

Qwen2.5-VL-7B (BF16): *10 v.s. 100 frames*

Time of First Token (TTFT)

Vision Tower: 10x

LLM Prefill: ~90x

N = num_frames * 391 + text_tokens

Self-attn: O(N^2 · d)

Compute-bound

Time Per Output Token(TPOT)

KV Cache: 10x

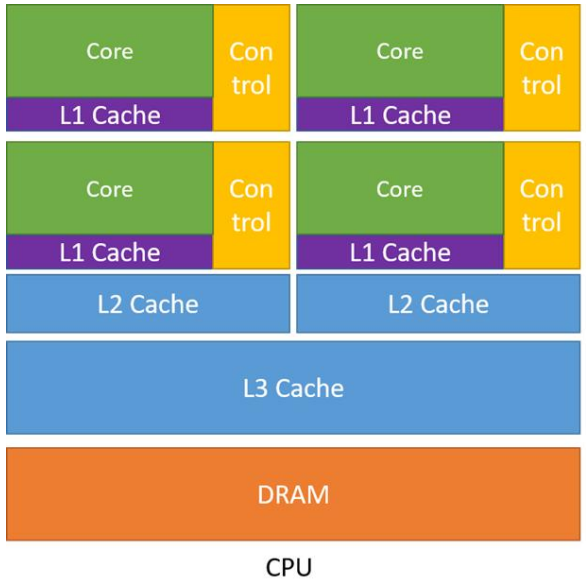
New Token Query (1 x d)

x

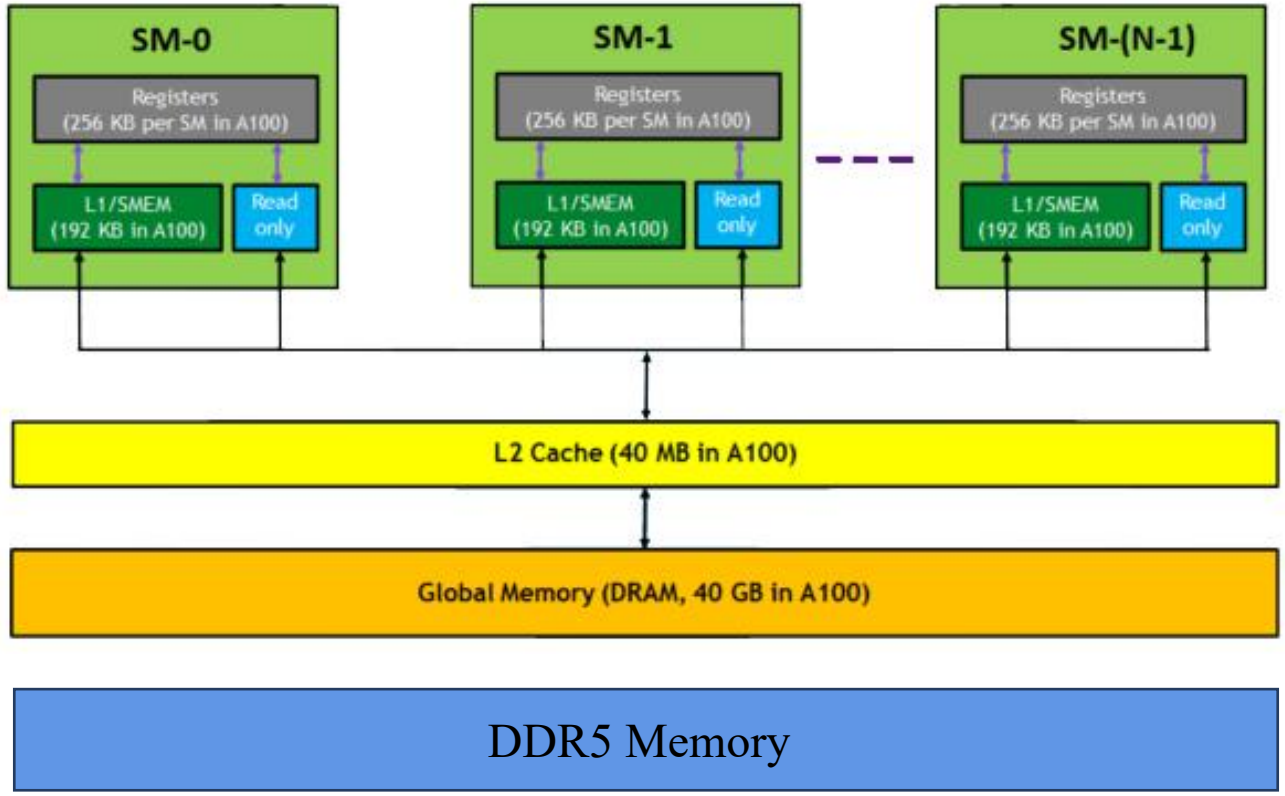
KV Cache (d x N)

Memory-bound

GPU Memory Hierarchy

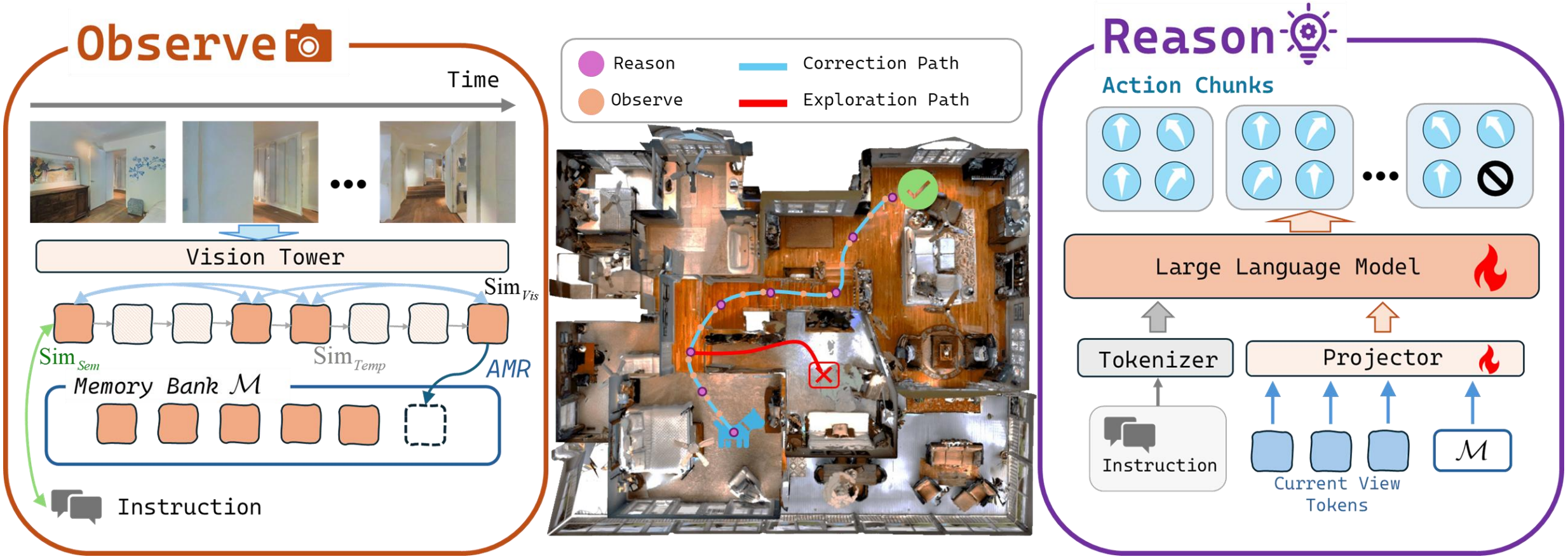


The GPU Devotes More Transistors to Data Processing



https://docs.nvidia.com/cuda/cuda-c-programming-guide/

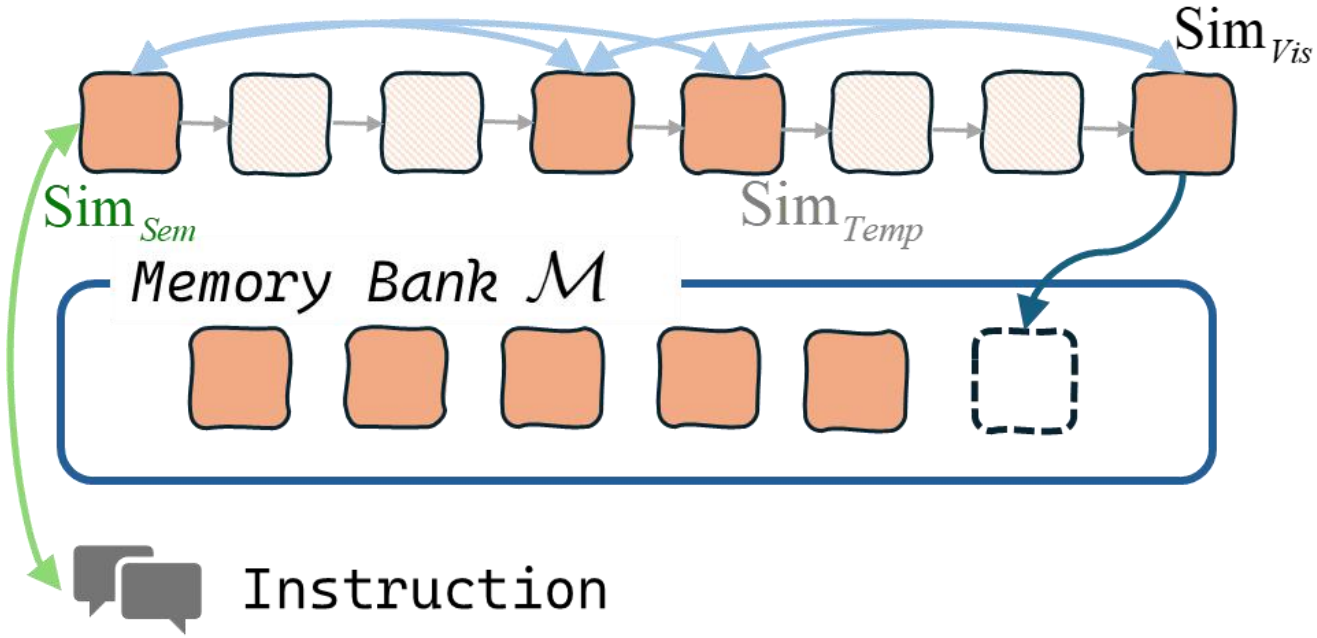
DecoVLN（Single-System, CVPR2026）



https://allenxinn.github.io/DecoVLN

DecoVLN（Single-System, CVPR2026）

Consider long-term memory as an optimization problem.



$$\mathrm{Sim}_{\mathrm{Vis}}(f, \mathcal{M}) = \max_{m \in \mathcal{M}} \left(\frac{\mathrm{embed}(f) \cdot \mathrm{embed}(m)}{\|\mathrm{embed}(f)\| \, \|\mathrm{embed}(m)\|} \right)$$

$$\mathrm{Sim}_{\mathrm{Sem}}(f, I) = \mathrm{sim}(\mathbf{e}_f, \mathbf{e}_I) = \frac{\mathbf{e}_f \cdot \mathbf{e}_I}{\|\mathbf{e}_f\| \, \|\mathbf{e}_I\|}$$

$$\mathrm{Sim}_{\mathrm{Temp}}(f, \mathcal{M}) = \frac{1}{\min_{m \in \mathcal{M}} |t_f - t_m| + \epsilon}$$

$$f^* = \arg \max_{f \in \mathcal{C} \setminus \mathcal{M}} [\lambda_R \cdot \mathrm{Sim}_{\mathrm{Sem}}(f, I) - (1 - \lambda_R) \cdot (w_V \cdot \mathrm{Sim}_{\mathrm{Vis}}(f, \mathcal{M}) + w_T \cdot \mathrm{Sim}_{\mathrm{Temp}}(f, \mathcal{M}))]$$

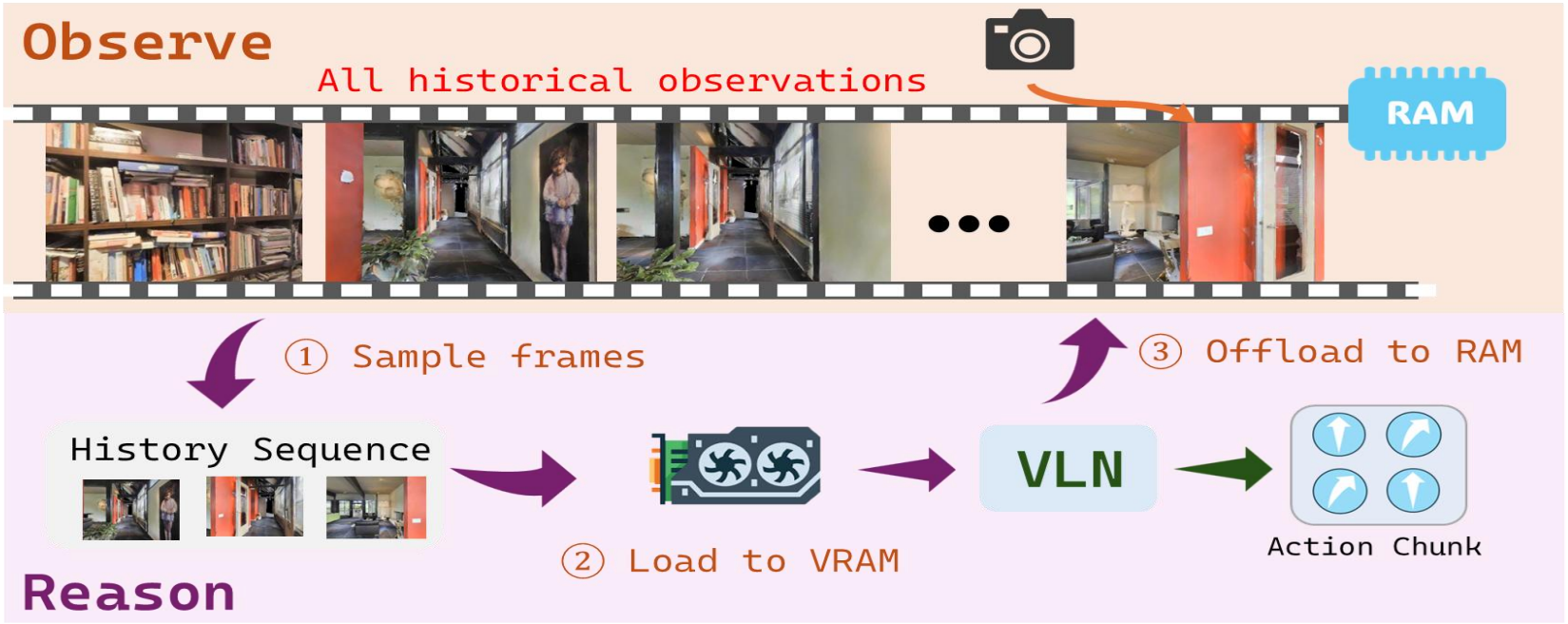
DecoVLN（Single-System, CVPR2026）

(a) Uniform Sampling

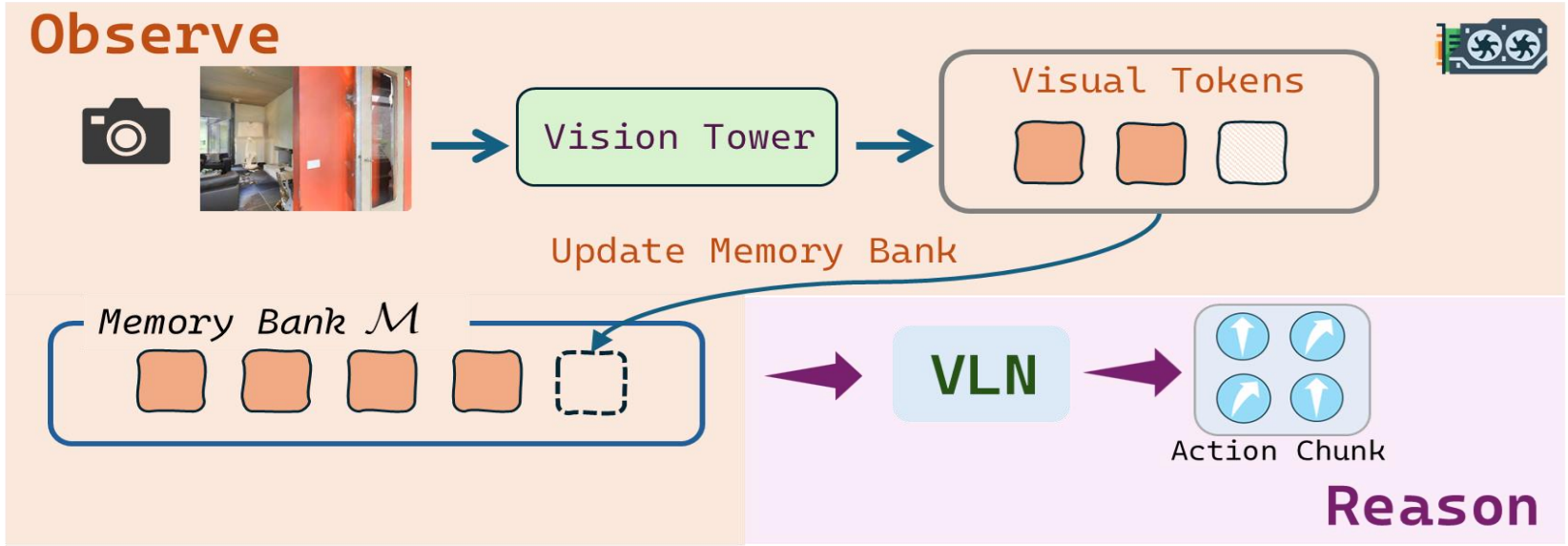
(b) Adaptive Memory Refinement

Now you are facing towards the wall, slightly turn to your right, you can see a open door to your right, exit room through an open door and move forward, there is a wall art to the left side of the wall and few steps in-front of you, walk down the steps and move forward, there are two black couches to your right, that's your end point.

DecoVLN（Single-System, CVPR2026）



Streaming Paradigm



DecoVLN

DecoVLN（Single-System, CVPR2026）

StreamVLN

DecoVLN

DecoVLN（Single-System, CVPR2026）

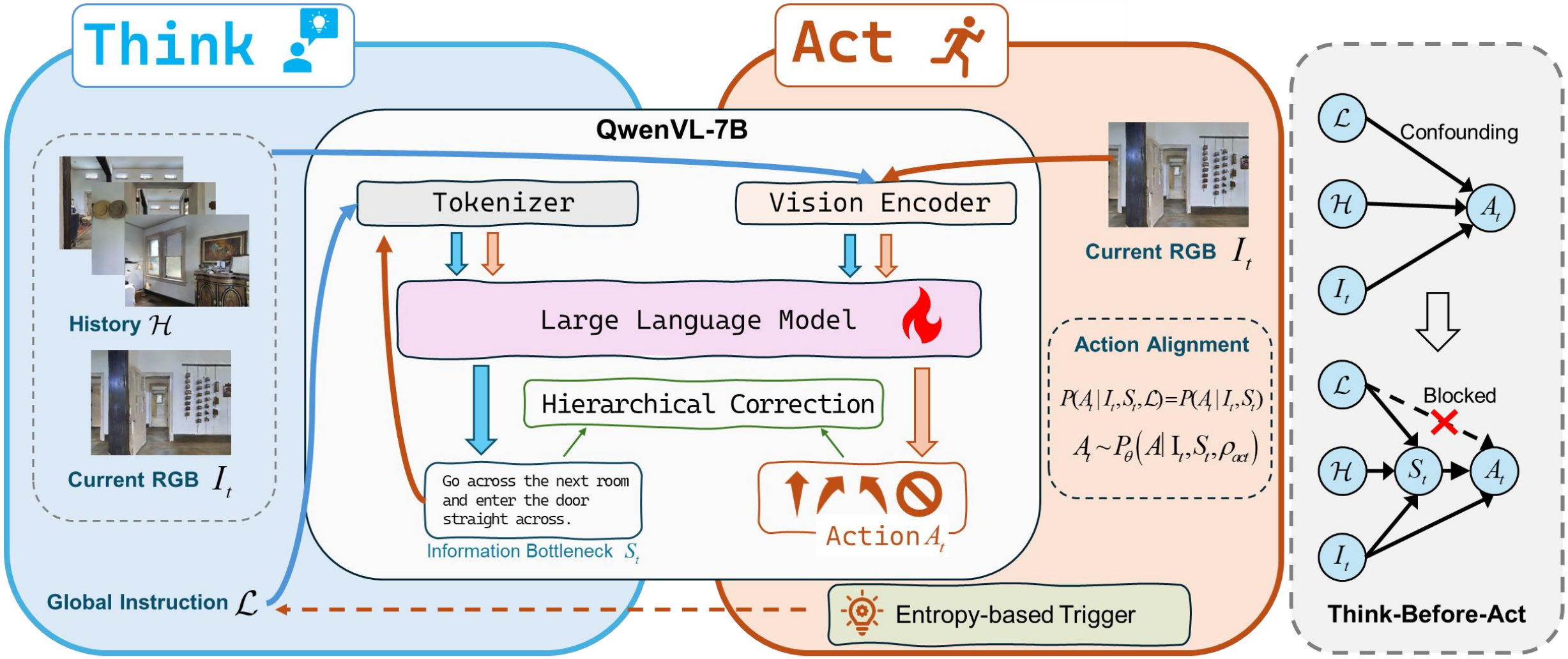
1. Expert Dataset: R2R, RxR (Stage 1)
2. Collect correction data using stage 1 model
3. Multi-Mode Dataset: Correction data + MM Datasets

Algorithm 1 Correction Data Collection

Require: Initial policy π_θ, expert policy π^*, dataset $\mathcal{D} = \{(P^i_{\text{exp}}, I^i)\}_{i=1}^{M}$, deviation threshold τ
Ensure: Correction dataset $\mathcal{D}_c$

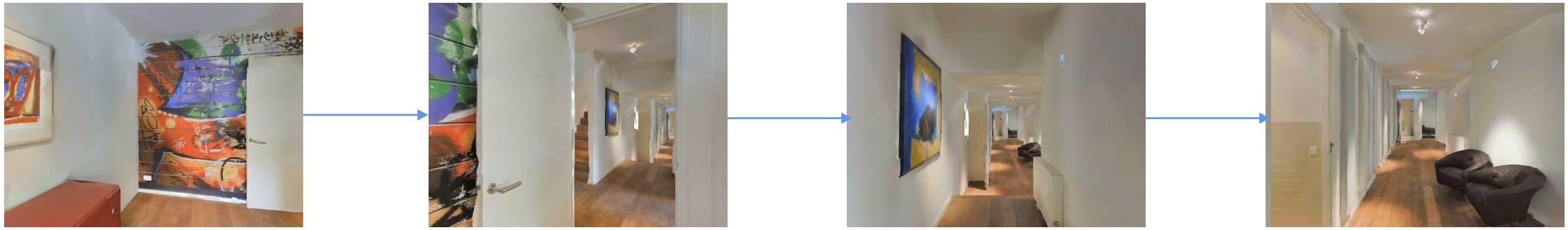
$\mathcal{D}_c \leftarrow \varnothing$ ▷ Initialize correction dataset
for all episode $(P_{\text{exp}}, I) \in \mathcal{D}$ **do**
  $P_{\text{exp}} \leftarrow \{s^*_0, s^*_1, \ldots, s^*_N\}$ ▷ Expert reference trajectory
  $H \leftarrow \varnothing$ ▷ Initialize memory state
  for $t = 0$ **to** $T_{\max}$ **do**
    $DM \leftarrow \min_{s^* \in P_{\text{exp}}} d_g(s_t, s^*)$ ▷ Compute deviation from expert trajectory
    if $0 < DM(s_t) \leq \tau$ **then**
      $a_t^{\text{exp}} \leftarrow \pi^*(s_t, P_{\text{exp}})$
      $\mathcal{D}_c \leftarrow \mathcal{D}_c \cup \{(s_t, a_t^{\text{exp}}, f_t)\}$ ▷ Store expert correction
    else if $DM(s_t) > \tau$ **then**
      break ▷ Abort episode due to large deviation
    end if
    $a_t \sim \pi_\theta(f_t, I, H)$ ▷ Roll out current policy
    $s_{t+1} \leftarrow \text{Env.Step}(a_t)$ ▷ Environment state update
    $f_{t+1} \leftarrow \text{Env.Observe}(s_{t+1})$ ▷ Acquire next observation
    $H \leftarrow \text{AMF}(H, f_{t+1})$ ▷ Adaptive memory refinement
    if target reached **or** episode failure **then**
      break ▷ Terminate episode
    end if
  end for
end for
return $\mathcal{D}_c$

IDEAL-VLN（Single-System）



Global Instruction Turn to your left and exit the room. Go across the next room and enter the door straight across. Stop once you enter the bathroom door.

IDEAL-VLN（Single-System）



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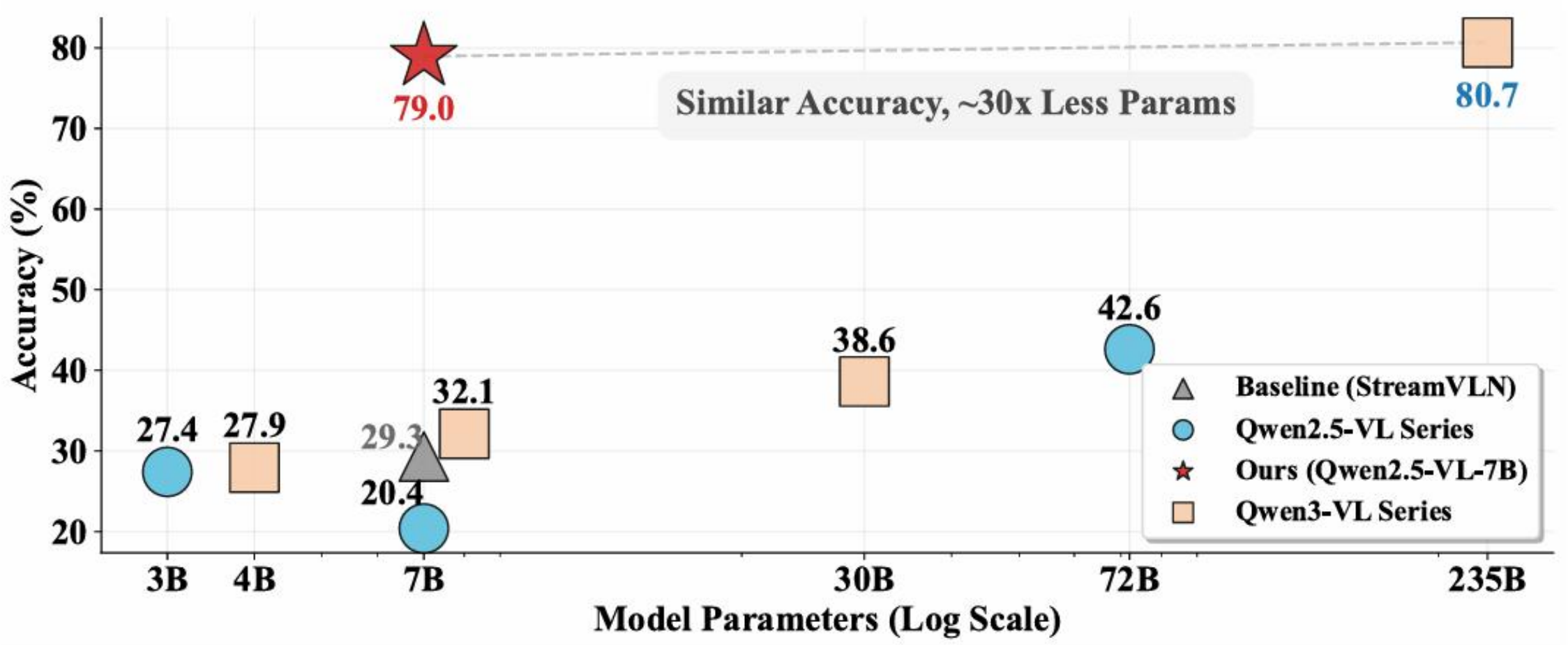
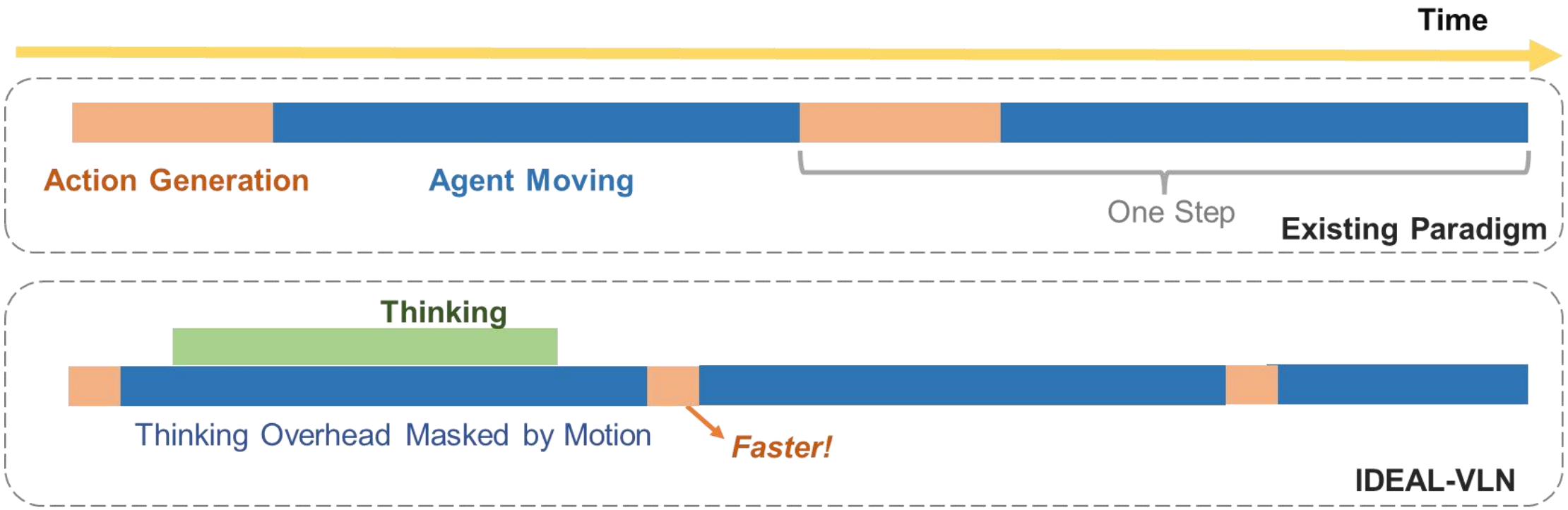
- ✗ Rule-Based Split (word count or period)
- ✗ Text Analysis and Split
- ✗ LLM-based Split

IDEAL-VLN（Single-System）



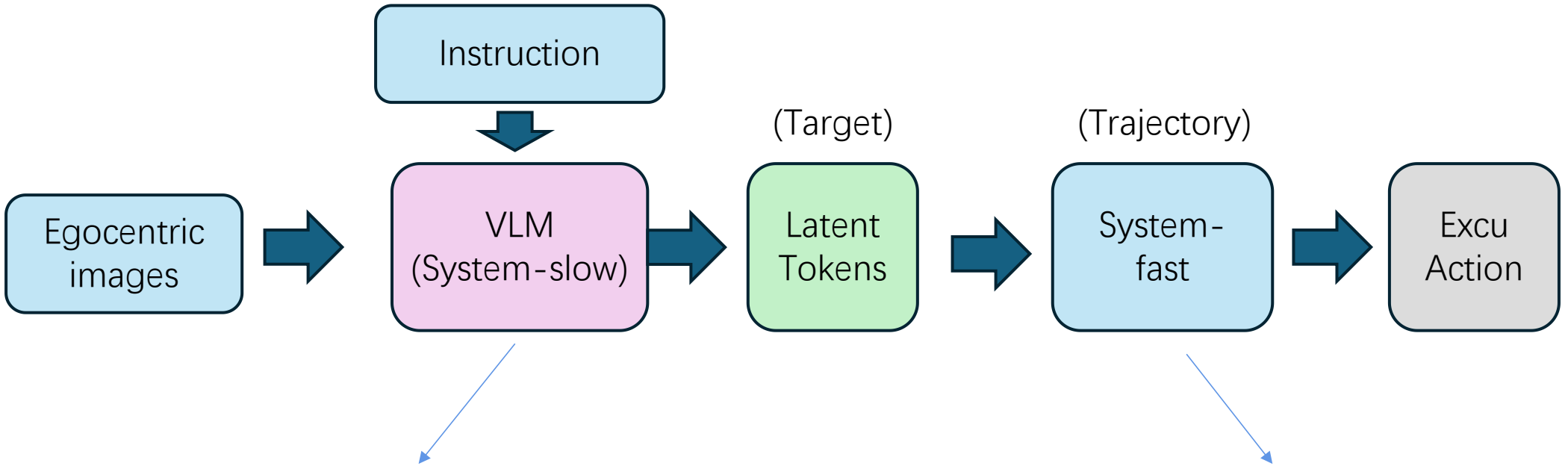
The existing models cannot comprehend the relationship between instructions and ego-centric images.

IDEAL-VLN（Single-System）



Method	Input tokens	Prefill Time(ms)	Steps/ Episode
Vanilla	7k	1625	21
Ours (Think)	7k	1832	5
Ours (Act)	2k	462	21

Dual-System VLN

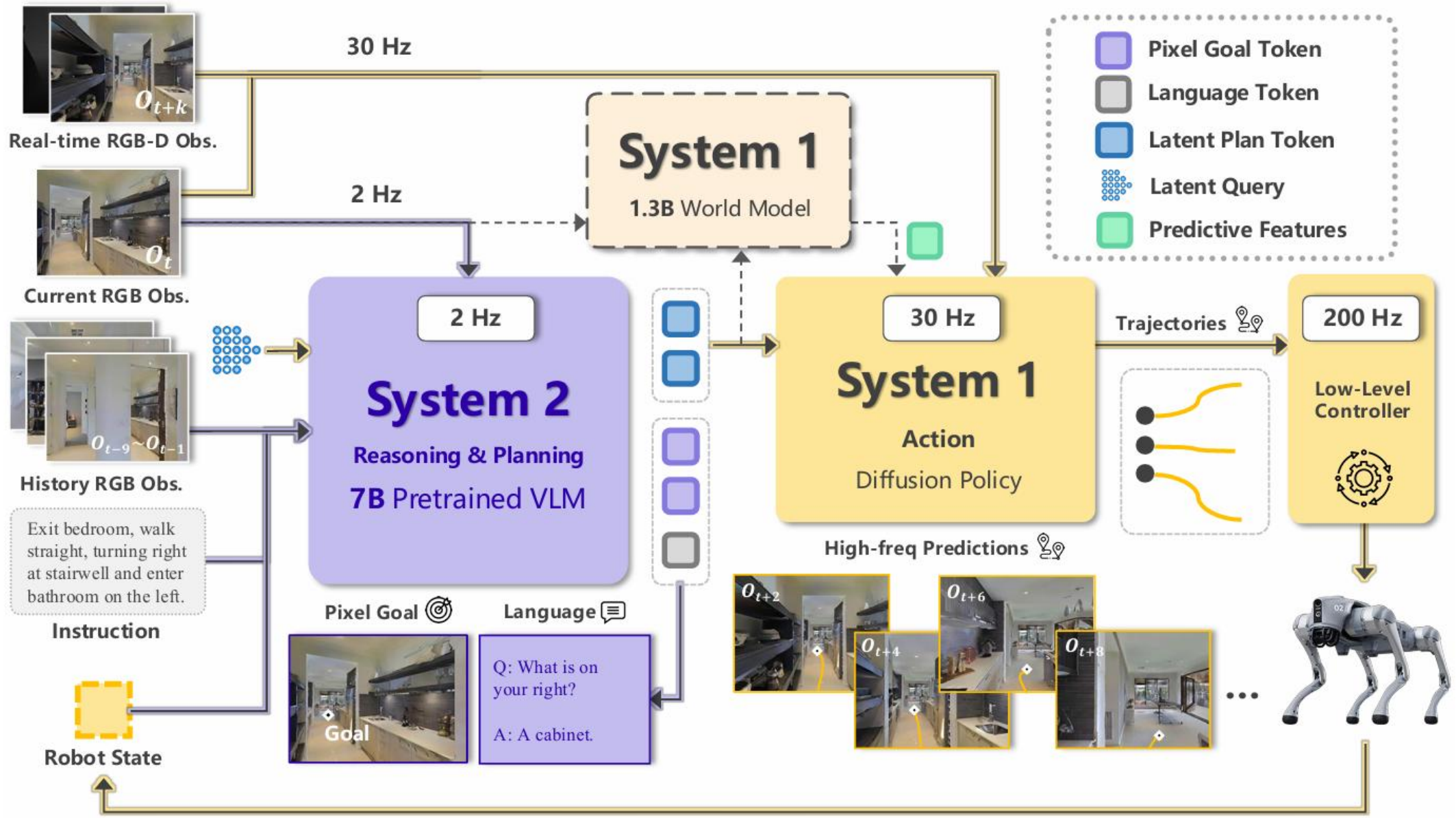


Only responsible for generating navigation points (image coordinate system)

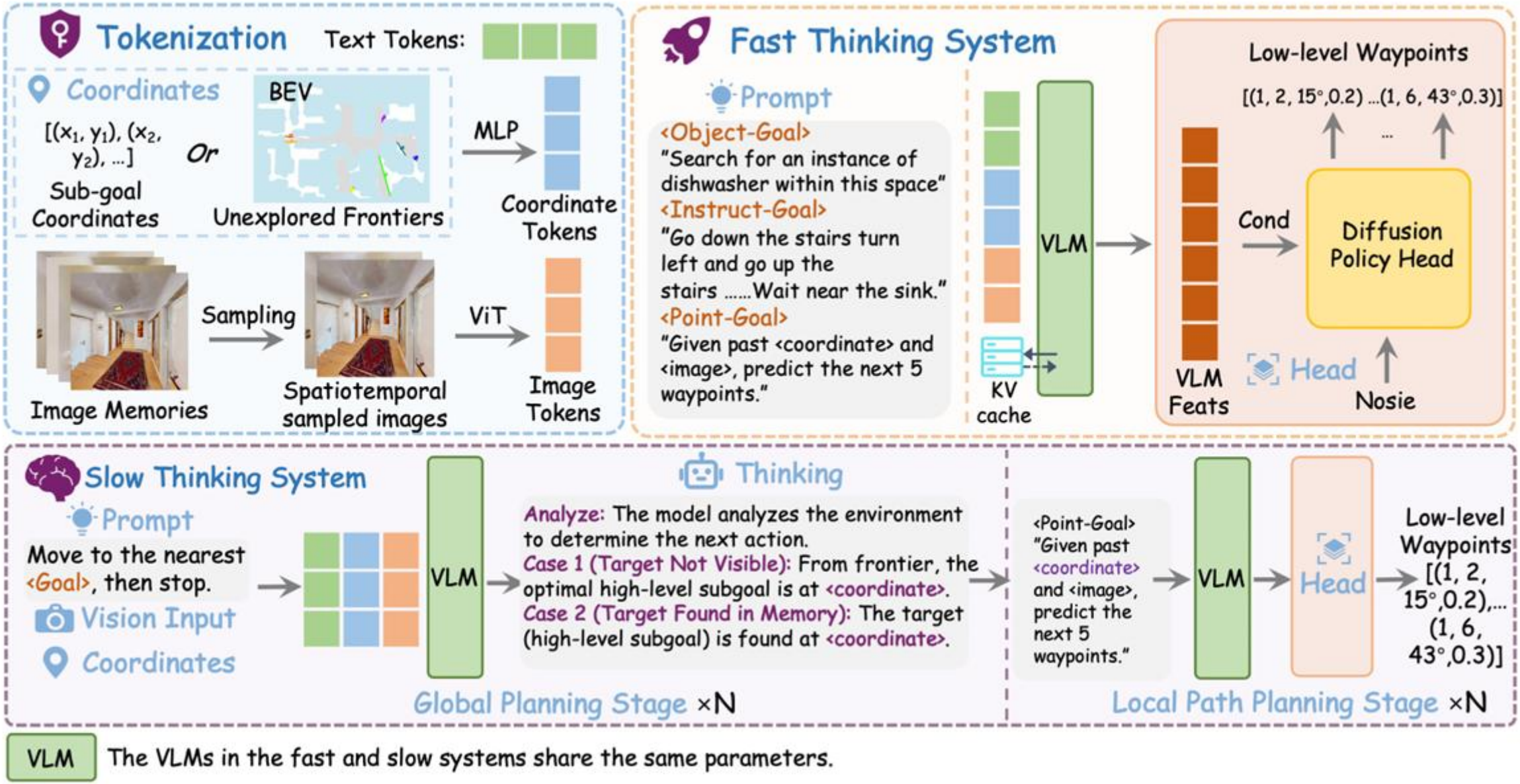
Convert the image coordinate into an executable trajectory

VLM is action-independent

DualVLN (ICLR 2026)



OmniNav (ICLR 2026)



Dual-System VLN

1. Joint training of the two systems is challenging
2. Incorrect navigation points may cause trajectory errors
3. Only available for specific robots
4. Very, very expensive

Dual-System VLN

A joint training scheme is particularly critical for Vision-and-Language Navigation (VLN), which requires strong general knowledge and semantic understanding, leading to substantial improvements in success rates in open environments. Stage 1 is trained with 96 NVIDIA H20 GPUs for 120 hours, and Stage 2 is trained with 64 NVIDIA H20 GPUs for 48 hours with lower learning rate.

-- OmniNav

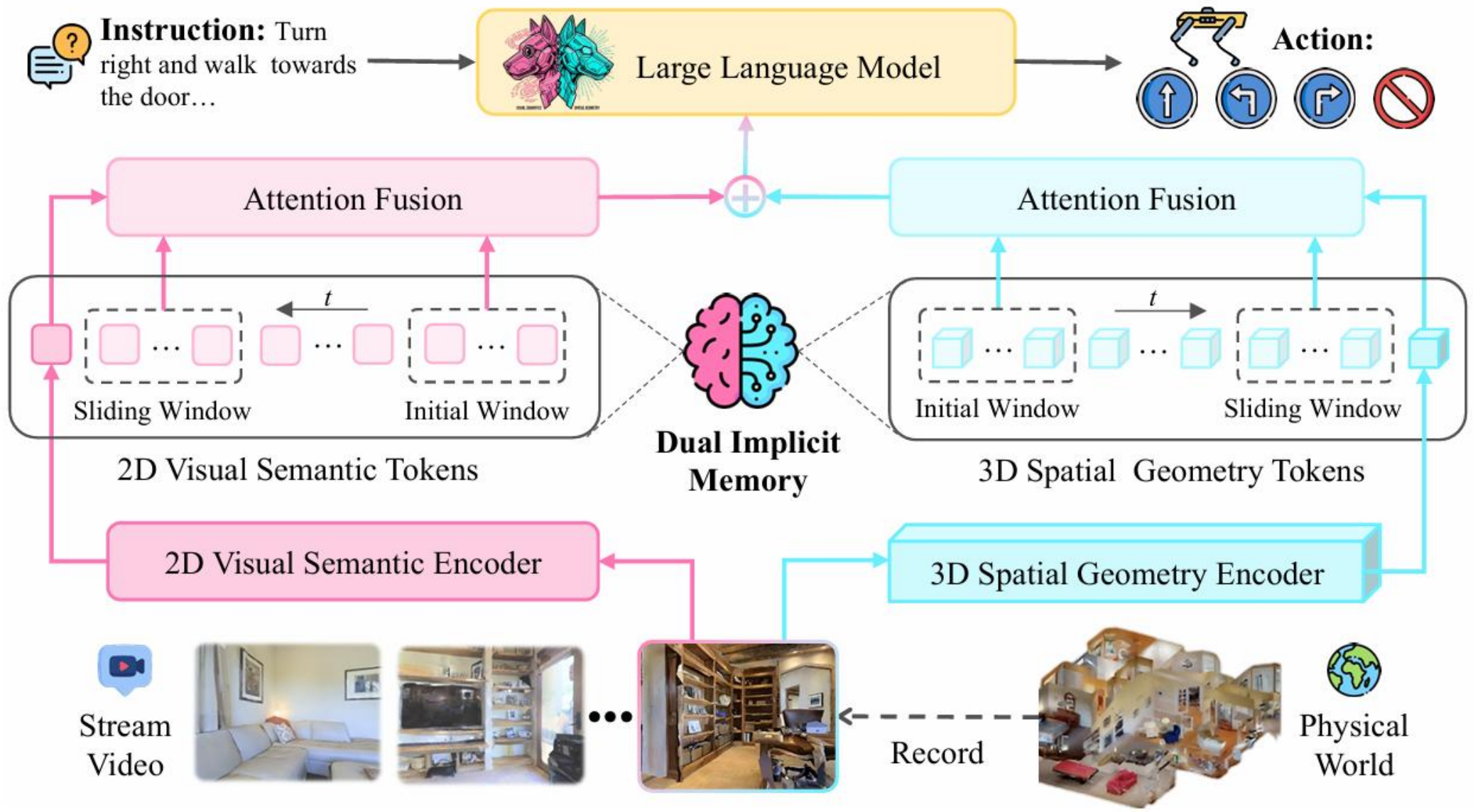
18000+ H20 hours
Dual-sys Training Cost: 15W+ RMB

Reproduction is extremely time-consuming

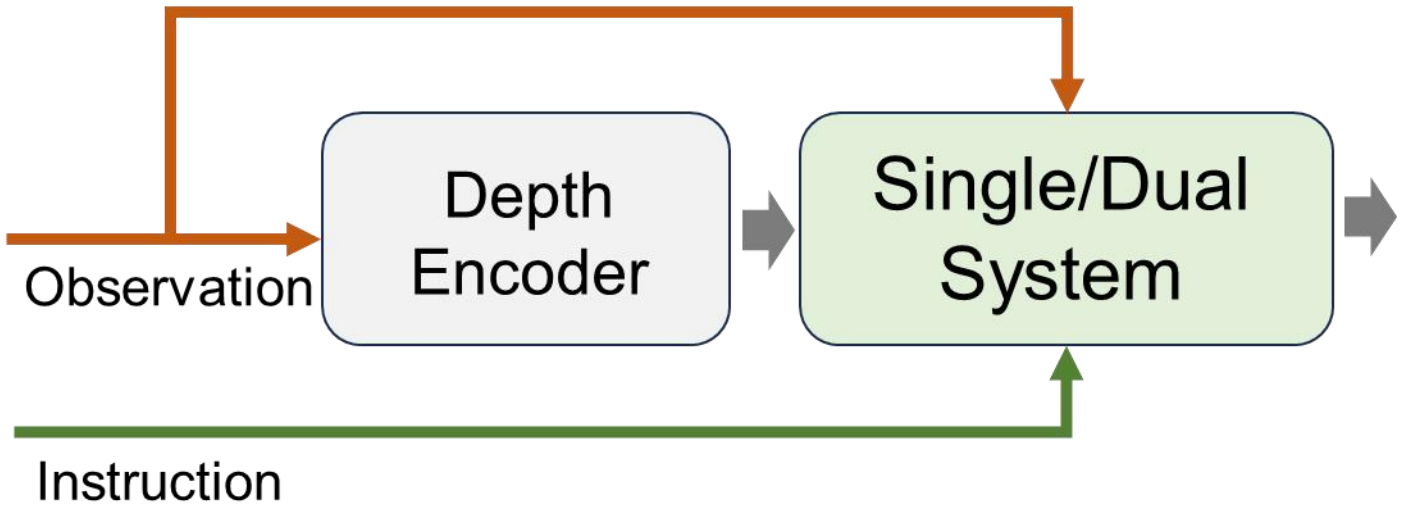
DecoVLN/ IDEAL-VLN: ~ 3k RMB

Depth Encoder-based Sys

JanusVLN (ICLR2026)



Depth Encoder-based Sys



Additional depth encoder required

Rely on depth encoder -> poor performance in real-world

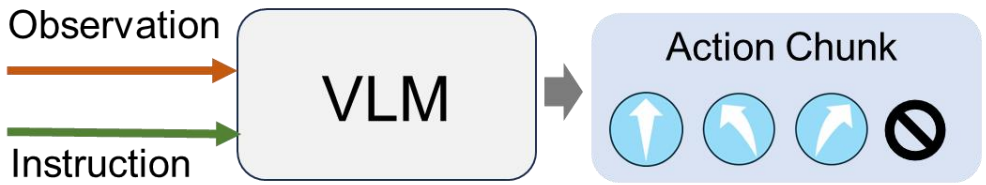
Significantly increases computational load and storage overhead

Depth Encoder-based Sys

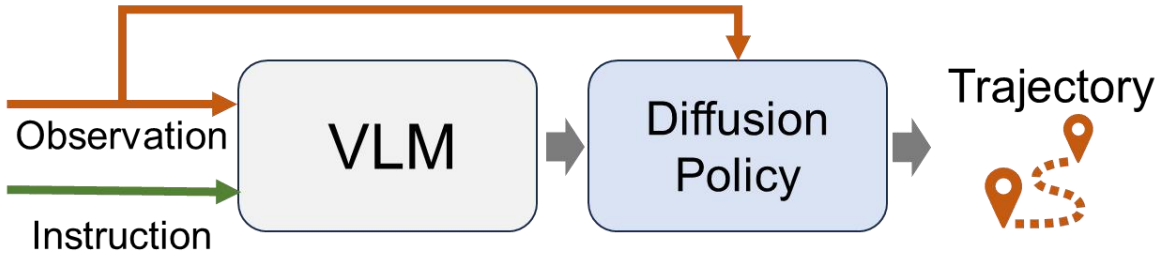
Why not use real depth map?

Depth map by realsense camera

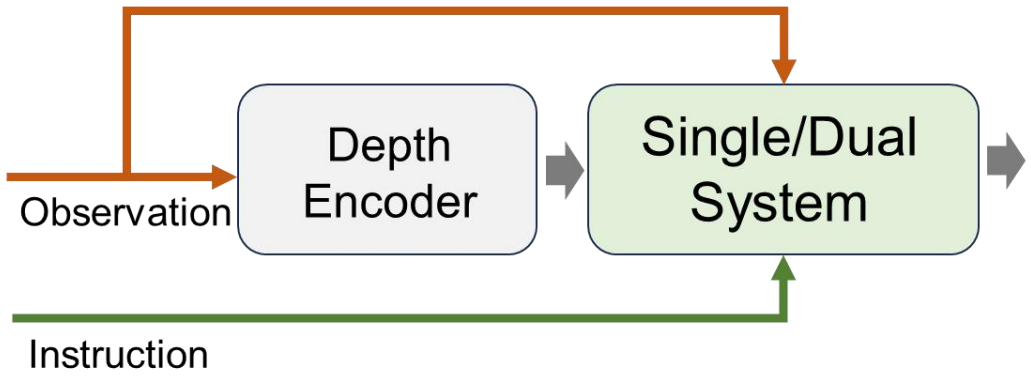
DepthAnything



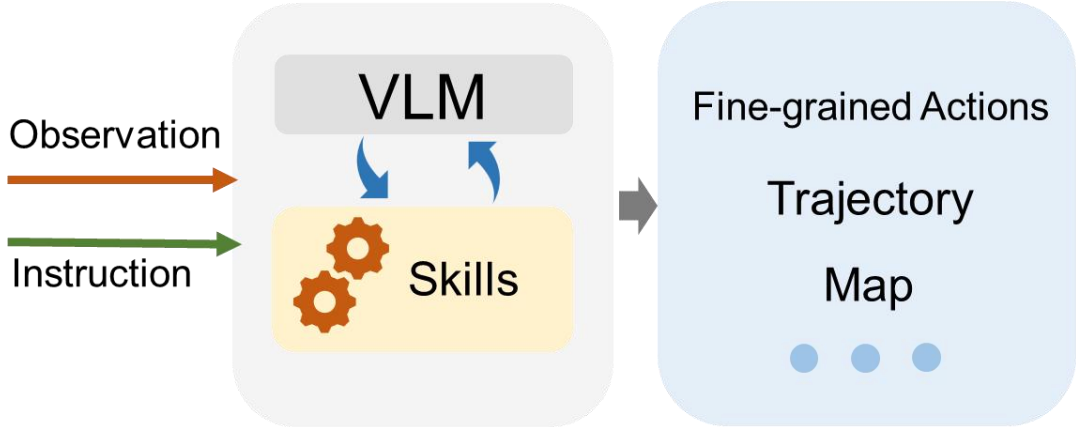
(a) Single-System



(b) Dual-System



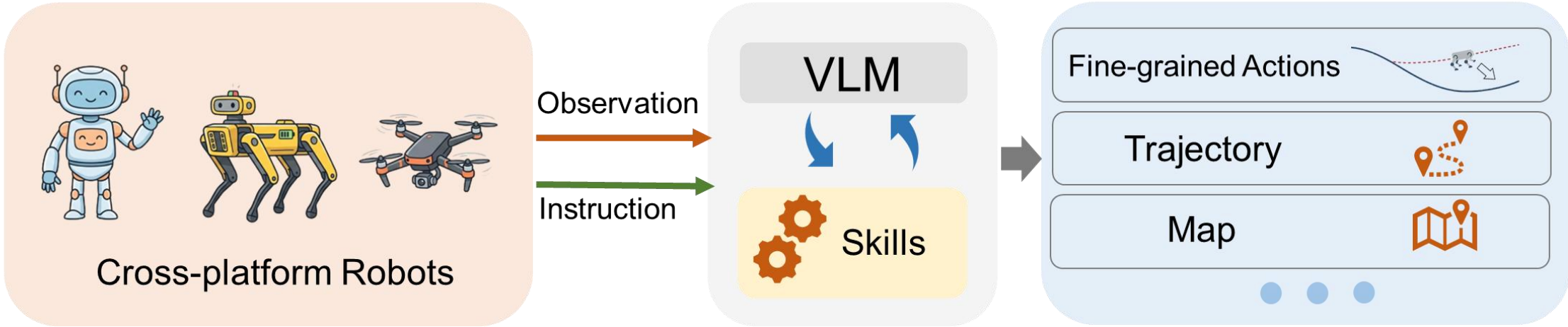
(c) Depth Encoder-based System



(d) AgentVLN

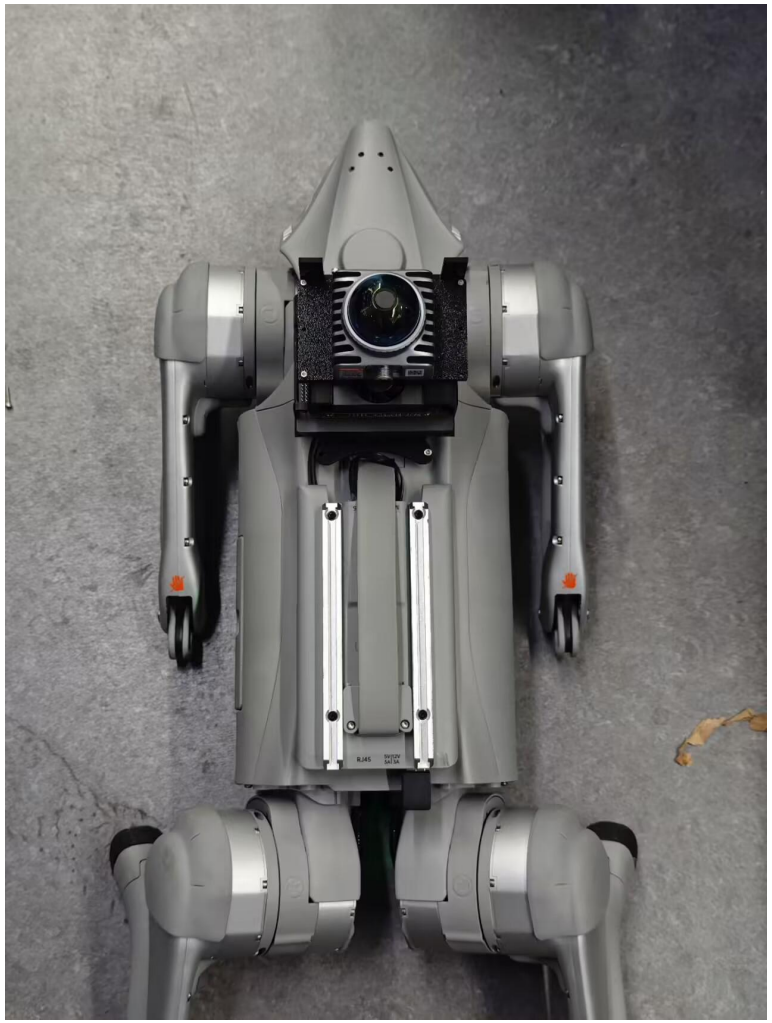
https://allenxinn.github.io/AgentVLN

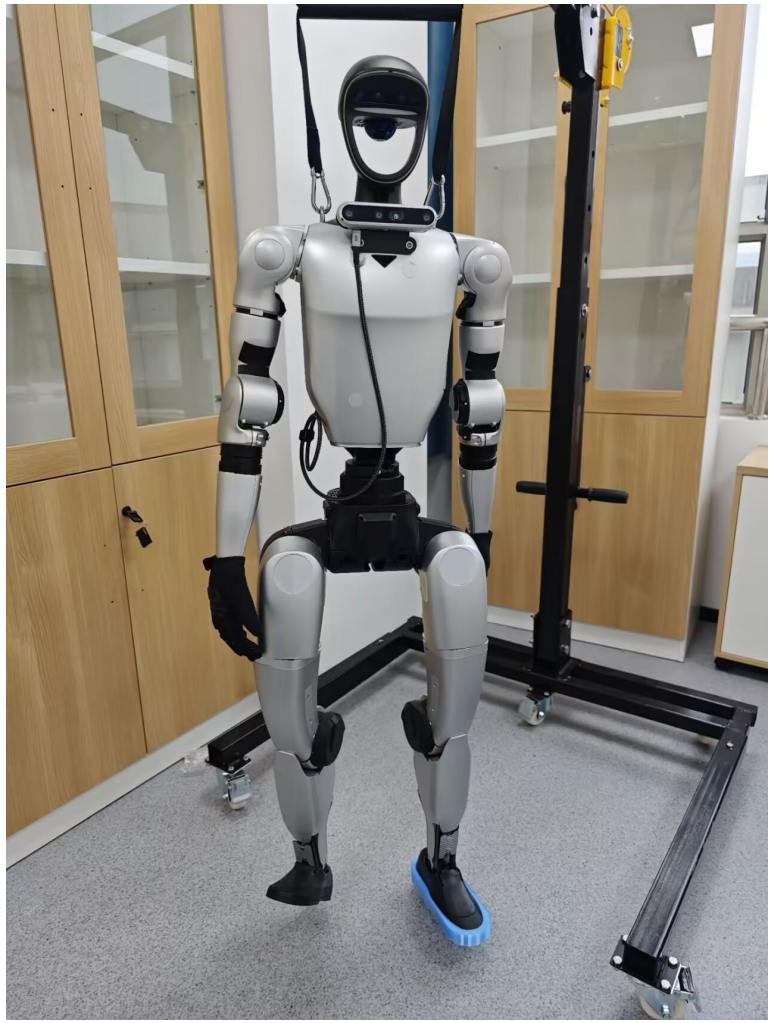
AgentVLN


Cross-platform Robots
Observation
Instruction
VLM
Skills
Fine-grained Actions
Trajectory
Map


633.0

AgentVLN



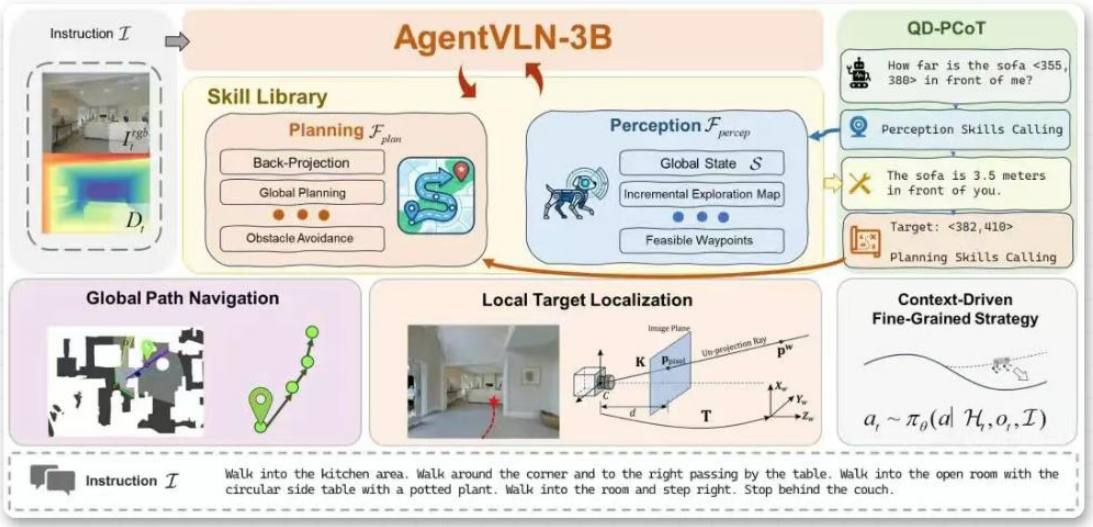


TODO

Quadrotor

小参数量，大能力！AgentVLN：轻量部署的下一代具身导航新范式

VLNer 视觉语言导航 2026年3月25日 21:50 湖南



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- **单位**：[1]南京航空航天大学，[2]山东大学，[3]浙江大学
- **论文标题**：AgentVLN: Towards Agentic Vision-and-Language Navigation
- **论文链接**：https://arxiv.org/abs/2603.17670v1
- **代码链接**：https://github.com/Allenxinn/AgentVLN

10k + views, 1k+ shares

AgentVLN：学会“自主导航”，轻量化具身视觉语言导航新范式！

原创 第一具身范式 具身智能之心TechDaily 2026年3月20日 17:32 上海

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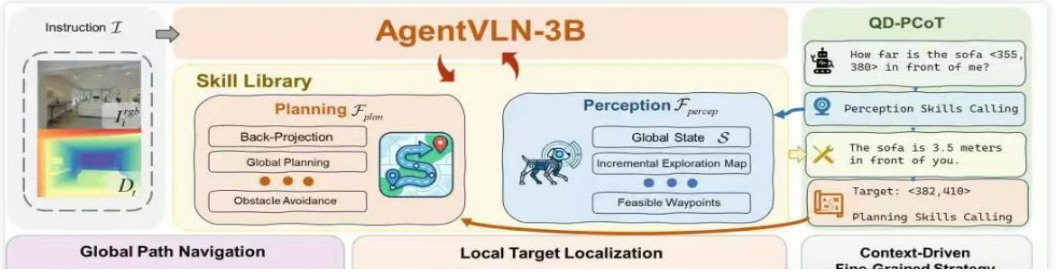
> 行业探讨：自主语言导航会终结室内SLAM，还是补齐SLAM最后的短板？

在具身智能的研究版图中，视觉语言导航（VLN）是**极具挑战性**(ps：好发文章)的方向之一——它要求智能体依托第一视角的动态视觉观测，遵循自然语言指令，在未知的三维物理环境中完成长时程的自主导航。*视觉语言模型（VLM）虽在二维语义理解上展现出强大能力，却始终难以突破三维空间感知不足、2D-3D表征错位、单目尺度模糊的瓶颈，让VLN系统的实际落地困难重重。*



智能体也能“看图说话”自主导航？AgentVLN突破视觉语言导航新边界

基本信息

- **作者**：Zihao Xin, Wentong Li, Yixuan Jiang, Ziyuan Huang, Bin Wang, Piji Li, Jianke Zhu, Jie Qin, Shengjun Huang
- **单位**：南京航空航天大学，山东大学，浙江大学
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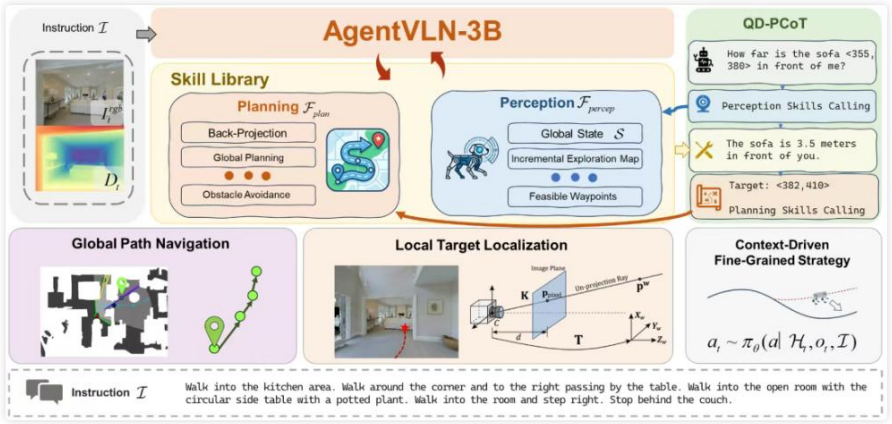
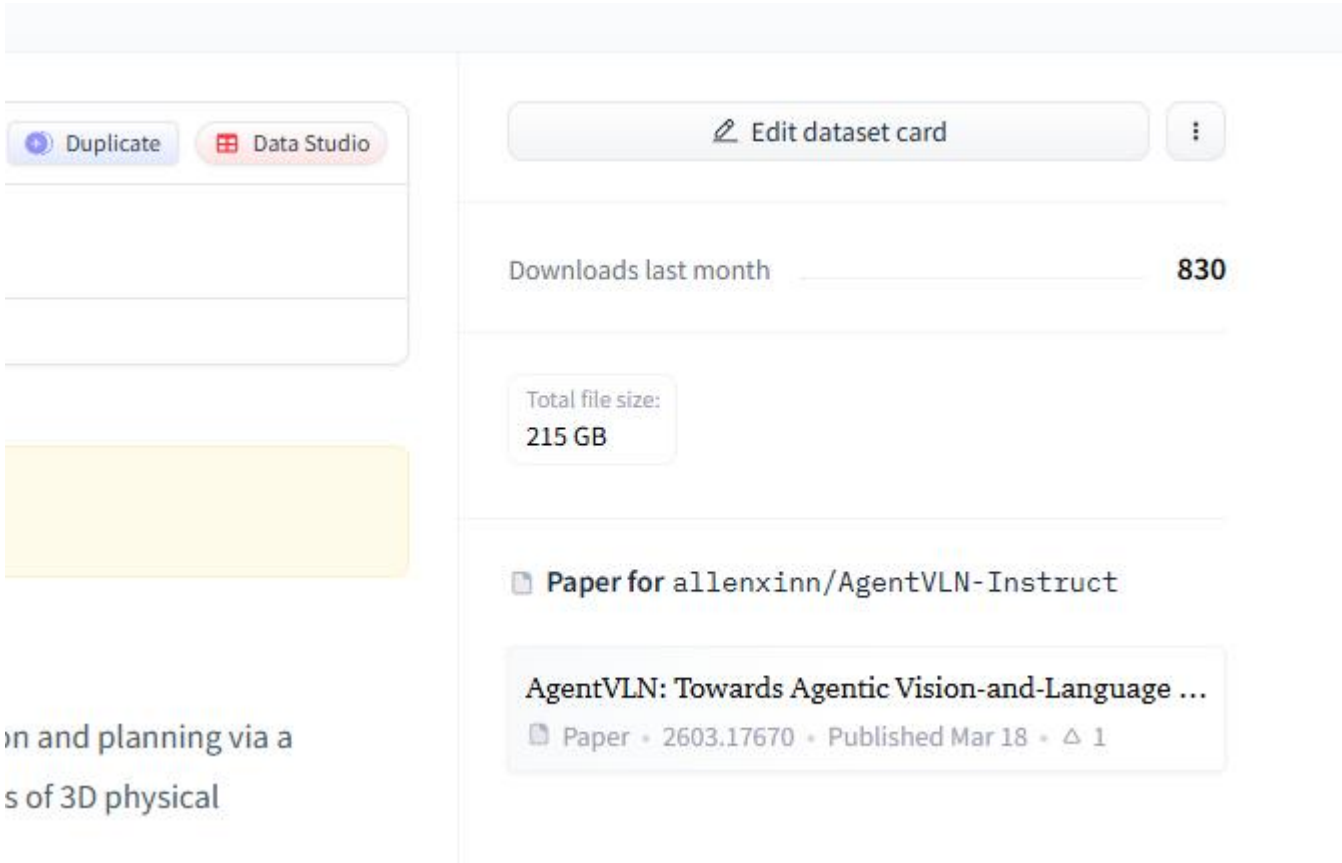
- **代码链接**：https://github.com/Allenxinn/AgentVLN

简要介绍



视觉语言导航（VLN）要求智能体根据复杂语言指令在未知环境中进行长距离导航。然而，现有系统常受



AgentVLN

Instruction $\mathcal{I}$

AgentVLN-3B

Skill Library

Planning $\mathcal{F}_{plan}$

- Back-Projection
- Global Planning
- ● ● ●
- Obstacle Avoidance

Perception $\mathcal{F}_{percep}$

- Global State $\mathcal{S}$
- Incremental Exploration Map
- ● ● ●
- Feasible Waypoints

QD-PCoT

How far is the sofa <355, 380> in front of me?

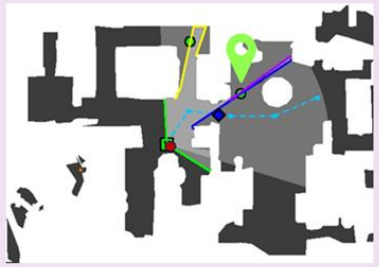
Perception Skills Calling

The sofa is 3.5 meters in front of you.

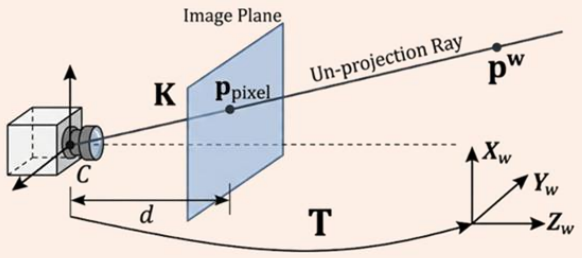
Target: <382,410>

Planning Skills Calling

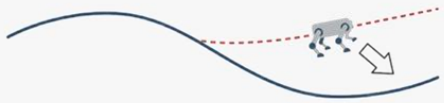
Global Path Navigation



Local Target Localization



Context-Driven Fine-Grained Strategy



$$a_t \sim \pi_\theta(a \mid \mathcal{H}_t, o_t, \mathcal{I})$$

Instruction $\mathcal{I}$

Walk into the kitchen area. Walk around the corner and to the right passing by the table. Walk into the open room with the circular side table with a potted plant. Walk into the room and step right. Stop behind the couch.

Duple Camera Sys

$$o_t = \{I_t^{rgb}, D_t\}$$

$$T_t = [R_t \mid \mathbf{t}_t] \in SE(3)$$

$$\mathbf{P}^w = R_t(d \cdot K^{-1}\mathbf{p}_{img}) + \mathbf{t}_t$$

$$s \cdot \mathbf{p}_{path}^{img} = KR_t^{-1}(\mathbf{P}_{path}^w - \mathbf{t}_t)$$

$$\mathbf{P}_{target}^c = d_{target} \cdot K^{-1}\mathbf{p}_{target}^{img} = \begin{bmatrix} \frac{(u_{target}-c_x)\cdot d_{target}}{f_x} \\ \frac{(v_{target}-c_y)\cdot d_{target}}{f_y} \\ d_{target} \end{bmatrix}$$

$$\mathbf{P}_{target}^w = R_t\mathbf{P}_{target}^c + \mathbf{t}_t$$

Lidar + Monocular Camera Sys

$$\mathbf{P}_{L,i} = R_W^L\mathbf{P}_{w,i} + \mathbf{t}_W^L$$

$$\mathbf{P}_{L,i} = R_W^L\mathbf{P}_{w,i} + \mathbf{t}_W^L$$

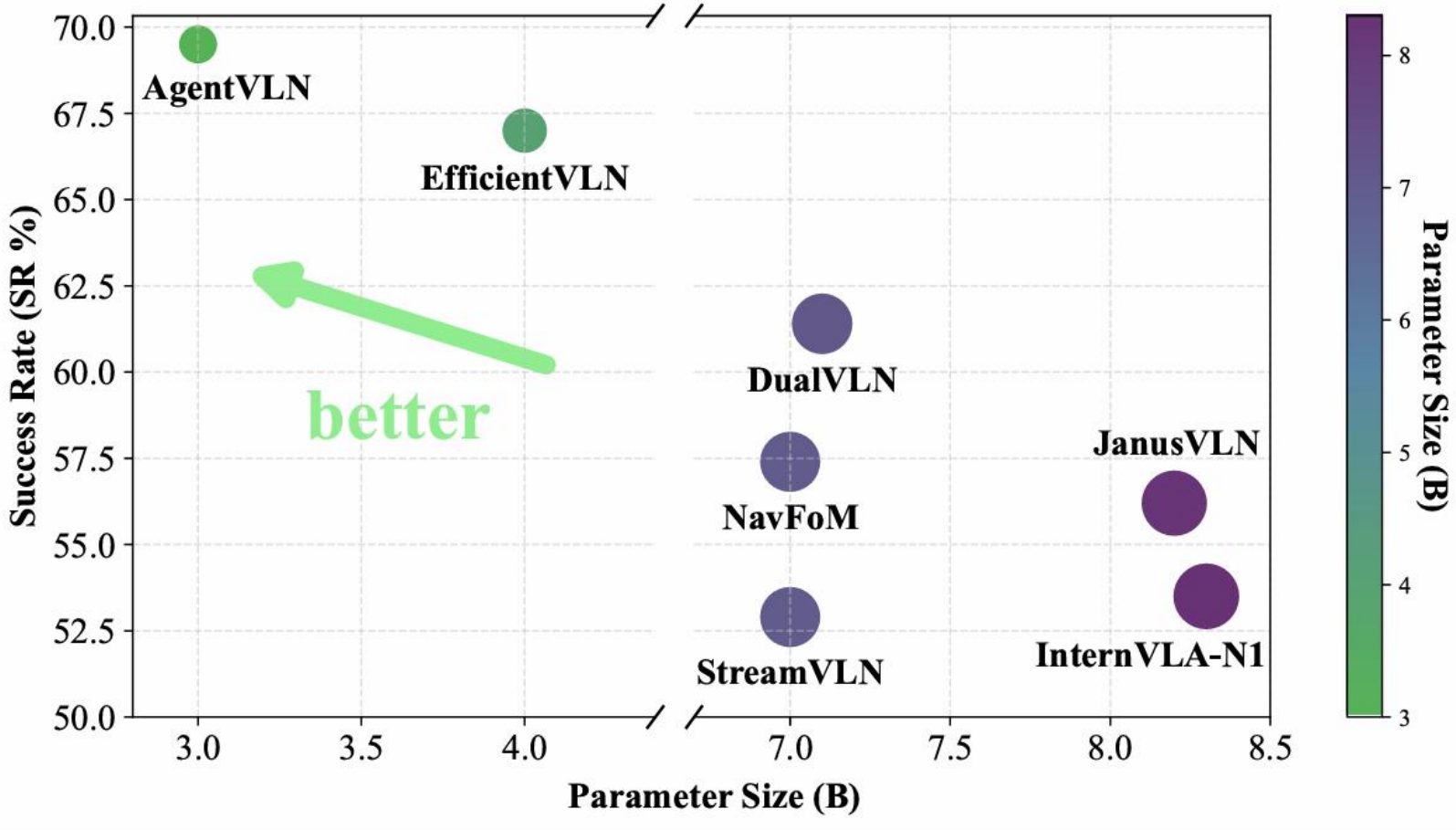
$$\mathbf{P}_{C,i} = R_L^C\mathbf{P}_{L,i} + \mathbf{t}_L^C$$

$$\hat{d} = \frac{\sum_{m=1}^{k} \omega_m \cdot d_m}{\sum_{m=1}^{k} \omega_m}$$

$$\omega_m = \frac{1}{\|\mathbf{p}_{target}^{img} - \mathbf{p}_m^{img}\|_2}$$

$$\mathbf{P}_{target}^C = \hat{d} \cdot K^{-1} \begin{bmatrix} u^* \\ v^* \\ 1 \end{bmatrix}$$

AgentVLN



Inference peak memory:

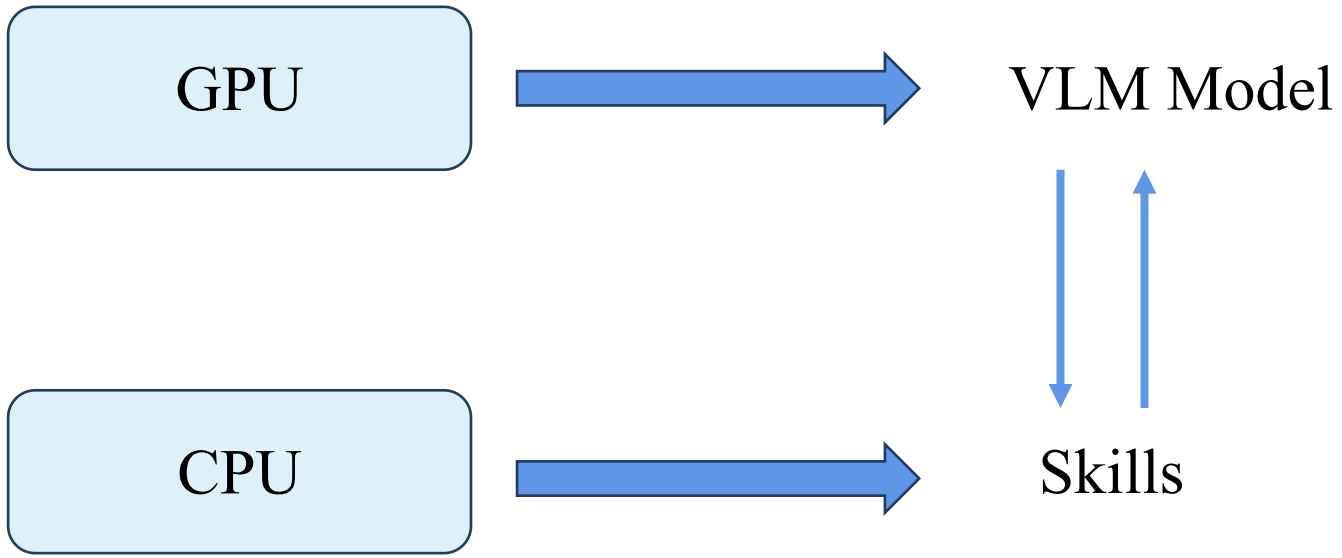
AgentVLN: ~9G

DualVLN: ~20G

StreamVLN: ~18G

The first VLN model deployable on embedded devices.

Outstanding load balancing



AgentVLN


Step: 0 [Plan]
Type: action
Dist: 13.7m
Pred: <action> TURN_RIGHT TURN_RIGHT TURN_RIGHT TURN_RIG


Start
End
Expert Path
Traveled
Targets
Nav Target

AgentVLN

Table 1: Comparison results with SOTA methods on the Val-Unseen dataset for R2R-CE. Our method outperforms other approaches on the same benchmarks, even having fewer parameters.

Method	Observation				R2R-CE			
	S.RGB	Pano.	Depth	Odo.	NE ↓	OS ↑	SR ↑	SPL ↑
HPN+DN [20]		✓	✓	✓	6.31	40.0	36.0	34.0
VLN BERT [17]		✓	✓	✓	5.74	53.0	44.0	39.0
CMA [17]		✓	✓	✓	6.20	52.0	41.0	36.0
Reborn [2]		✓	✓	✓	5.40	57.0	50.0	46.0
Ego^2-Map [18]		✓	✓	✓	5.54	56.0	47.0	41.0
DreamWalker [39]		✓	✓	✓	5.53	59.0	49.0	44.0
ETPNav [1]		✓	✓	✓	4.71	65.0	57.0	49.0
Seq2Seq [21]	✓		✓		7.77	37.0	25.0	22.0
RGB-CMA [21]	✓				9.55	10.0	5.0	4.0
AG-CMTP [8]		✓	✓		7.90	39.0	23.0	19.0
R2R-CMTP [8]		✓	✓		7.90	38.0	26.0	22.0
LAW [35]	✓		✓	✓	6.83	44.0	35.0	31.0
CM2 [14]	✓		✓		7.02	41.0	34.0	27.0
WS-MGMap [9]	✓		✓		6.28	47.0	38.0	34.0
ETPNav+FF [42]	✓		✓		5.95	55.8	44.9	30.4
AO-Planner [7]		✓	✓		5.55	59.0	47.0	33.0
NaVid-7B [51]	✓				5.47	49.0	37.0	35.0
Uni-NaVid-7B [50]	✓				5.58	53.3	47.0	42.7
NaVILA-7B [12]	✓				5.22	62.5	54.0	49.0
StreamVLN-7B [44]	✓				5.10	64.0	55.7	50.9
NavFoM-7B [49]	✓				5.01	64.9	56.2	51.2
JanusVLN-8.2B [48]	✓				4.78	65.2	60.5	56.8
EfficientVLN-4B [53]	✓				4.18	**73.7**	64.2	55.9
DualVLN-7.1B [43]	✓				4.05	70.7	64.3	58.5
StreamVLN-7B [44]	✓		✓		4.98	64.2	56.9	51.9
InternVLA-N1-8.3B [38]	✓		✓		4.83	63.3	58.2	54.0
AgentVLN-3B	✓		✓		**3.88**	73.5	**67.2**	**64.7**

Table 2: Comparison with SOTA methods on RxR-CE Val-Unseen split.

Method	S.RGB	Pano.	Depth	Odo.	NE ↓	SR ↑	SPL ↑	nDTW ↑
VLN BERT [17]		✓	✓	✓	8.98	27.0	22.6	46.7
CMA [17]		✓	✓	✓	8.76	26.5	22.1	47.0
Reborn [2]		✓	✓	✓	5.98	48.6	42.0	63.3
ETPNav [1]		✓	✓	✓	5.64	54.7	44.8	61.9
Seq2Seq [21]	✓		✓		12.10	13.9	11.9	30.8
LAW [35]	✓		✓	✓	10.90	8.0	8.0	38.0
ETPNav+FF [42]	✓		✓	✓	8.79	25.5	18.1	-
AO-Planner [7]		✓	✓		7.06	43.3	30.5	50.1
Uni-NaVid-7B [50]	✓				6.24	48.7	40.9	-
NaVILA-7B [12]	✓				6.77	49.3	44.0	58.8
NavFoM-7B [49]	✓				5.51	57.4	49.4	60.2
JanusVLN-8.2B [47]	✓				6.06	56.2	47.5	62.1
StreamVLN-7B [44]	✓				6.16	51.8	45.0	61.9
InternVLA-N1-7B [13]	✓				6.41	49.5	41.8	62.6
EfficientVLN-4B [53]	✓				**3.88**	67.0	54.3	68.4
DualVLN-7.1B [43]	✓				4.58	61.4	51.8	70.0
StreamVLN-7B [44]	✓		✓		6.22	52.9	46.0	61.9
InternVLA-N1-8.3B [38]	✓		✓		5.91	53.5	46.1	65.3
AgentVLN-3B	✓		✓		3.92	**69.5**	**61.3**	**74.6**

Future Work: Infinite Memory

Model architecture specifically designed for VLN tasks.

Static Memory: $H^I = \text{EncodeOnce}(I), \qquad M_I = K_I^{(l)}, V_I^{(l)}$

Dynamic Memory: $h_t^{loc} = \text{SWA}(o_{t-K:t}, a_{t-K:t-1}, p_{t-K:t})$

Memory Update:

$$e_t = \text{WriteMLP}(h_t^{loc}, a_{t-1}, p_t)$$

$$S_t = \text{GatedDeltaNetWithDecay}(S_{t-1}, e_t)$$

$$h_t^{hist} = \text{Read}(S_t, q_t^{hist})$$

$$S_t = \rho_t \odot S_{t-1}\left(I - \beta_t k_t k_t^\top\right) + \beta_t v_t k_t^\top$$

Future Work: Infinite Memory

Model architecture specifically designed for VLN tasks.

Sliding Attention + GDN Attention

Peak memory usage: 5.5G
Achieve 10 FPS
Inference Delay: 0.45s
No inference optimization was performed!