
CS586 (25 Spring) : Student Lecture

Vision-Language Model (VLM) for embodied navigation

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KAIST

The KAIST logo consists of the letters "KAIST" in a bold, blue, sans-serif font. Below the text is a light blue horizontal oval shape that serves as a shadow or base for the letters.

Review

Navigation with Probabilistic Generative Models: About Efficient Conditioning and its Architectures

	Diffusion	Flow Matching
Process	Step-by-step noise addition and denoising	Continuous transformation via Velocity fields
Mathematical Base	Stochastic process	Deterministic ODE
Sampling	Many steps	Few steps
Best for	High-fidelity, complex generation	Fast, controllable planning

Embodied Navigation

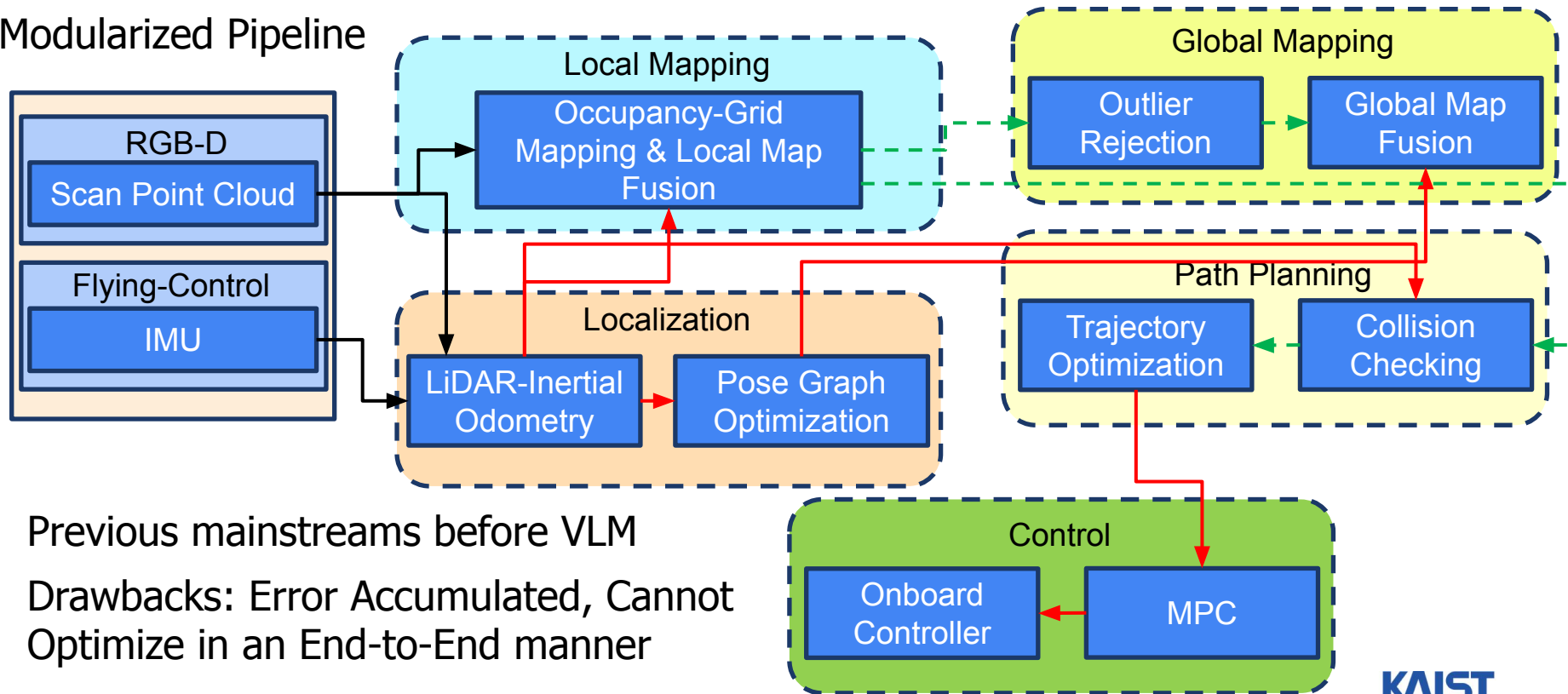
Task definition

Embodied Navigation: A physically agent autonomously accomplish a user-specified task in a 3-D environment — **without** access to a **privileged global map**.

The agent perceives the world only through its egocentric sensors (RGB-D, LiDAR, etc.), maintains internal memory, and decides a sequence of actions (e.g., turn \leftrightarrow , move \updownarrow , or Chain-of-Thought) that bring it finish the task.

Previous Embodied Navigation

Modularized Pipeline

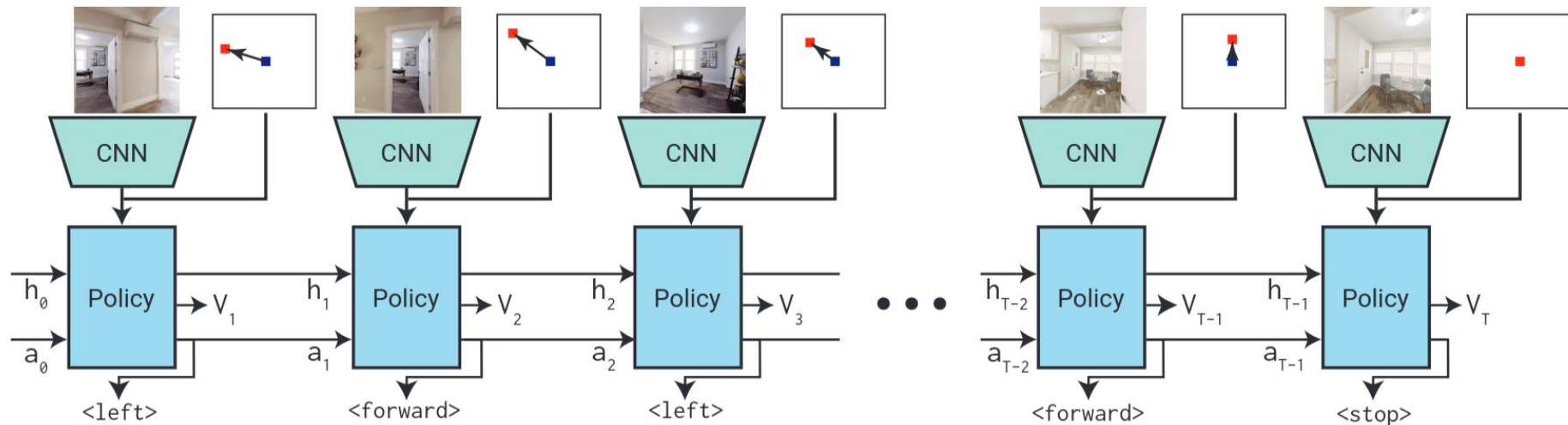


Previous mainstreams before VLM

Drawbacks: Error Accumulated, Cannot Optimize in an End-to-End manner

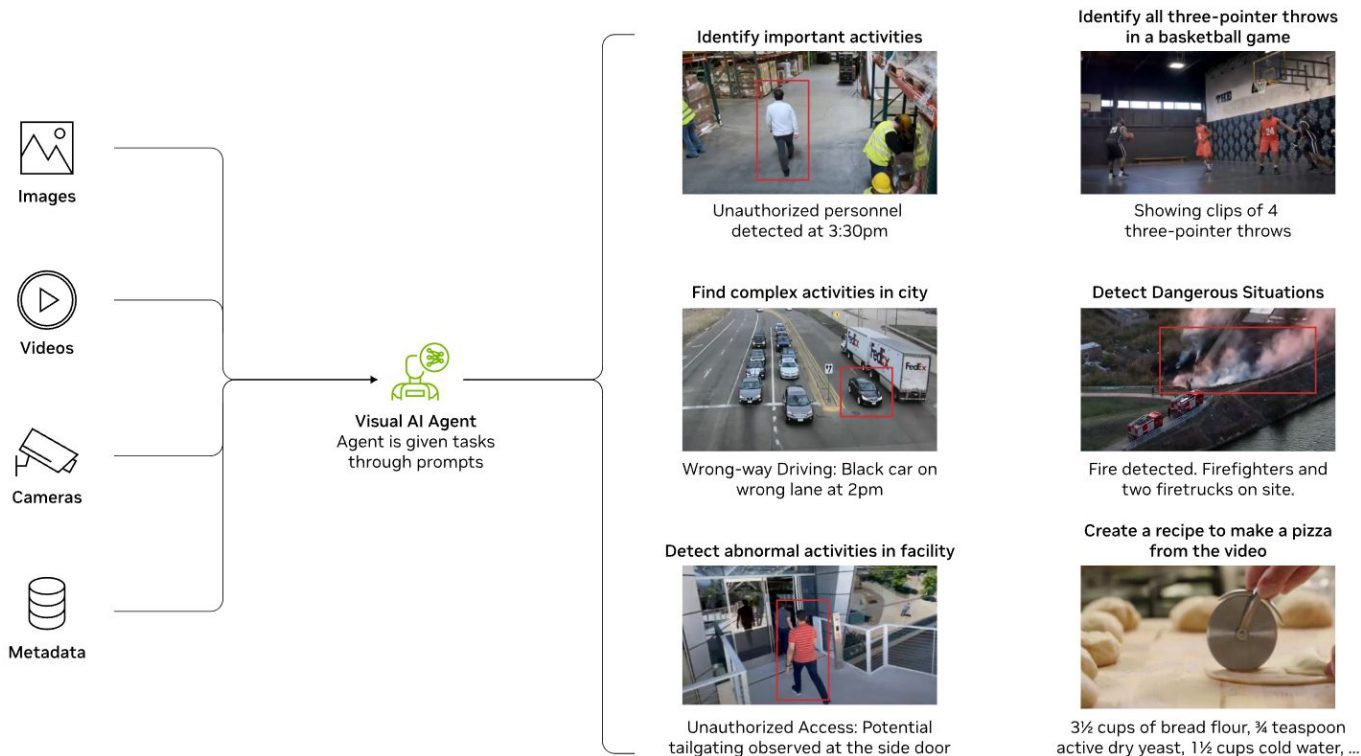
Previous Embodied Navigation

Reinforcement Learning-based Navigation



Drawbacks: Low Sample Efficiency, Poor Generalization Ability, Large Sim2Real Gap

Vision-Language Model (VLM)

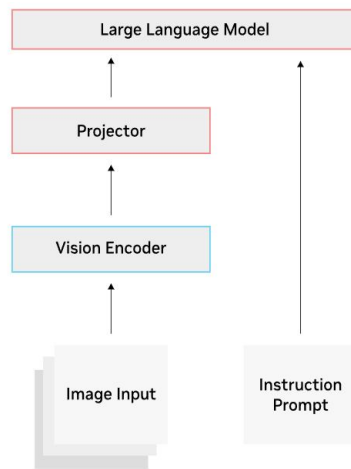
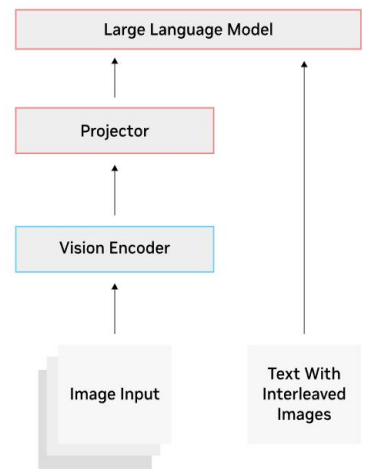
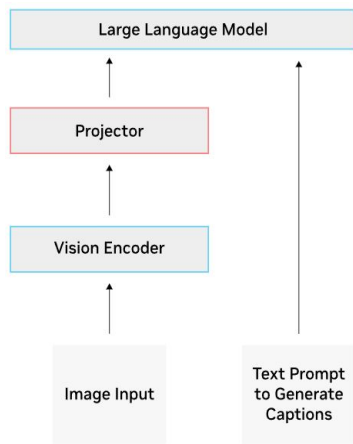
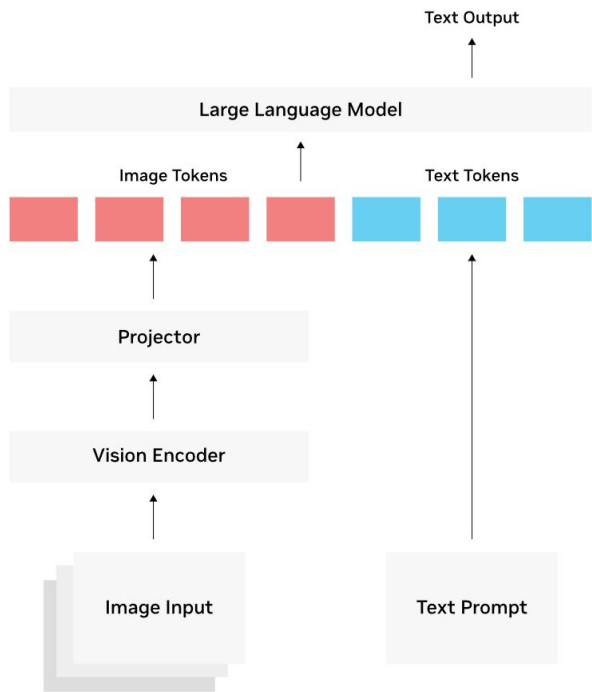


VLMs:

Multimodal AI systems built by combining a LLM with a vision encoder, giving the LLM the ability to “**see.**”

With this ability, VLMs can process and provide advanced understanding of **video**, **image**, and **text** inputs supplied in the prompt to generate text responses.

Vision-Language Model (VLM)



- The layers of the VLM that are updated during the training stage
- The layers of the VLM that are not updated during the training stage

VLM4Navigation

Navigation before VLM

1. Reinforcement Learning or Imitation Learning
2. No Language Grounding ability
3. Lack of open-world generalization ability
4. Large Sim2Real gap

What VLM brings

1. Vision-Language Efficient Fusion
2. Improved Semantic Understanding ability
3. Significantly improved zero-shot ability
4. Cross-Task transfer become available

VLM4Navigation

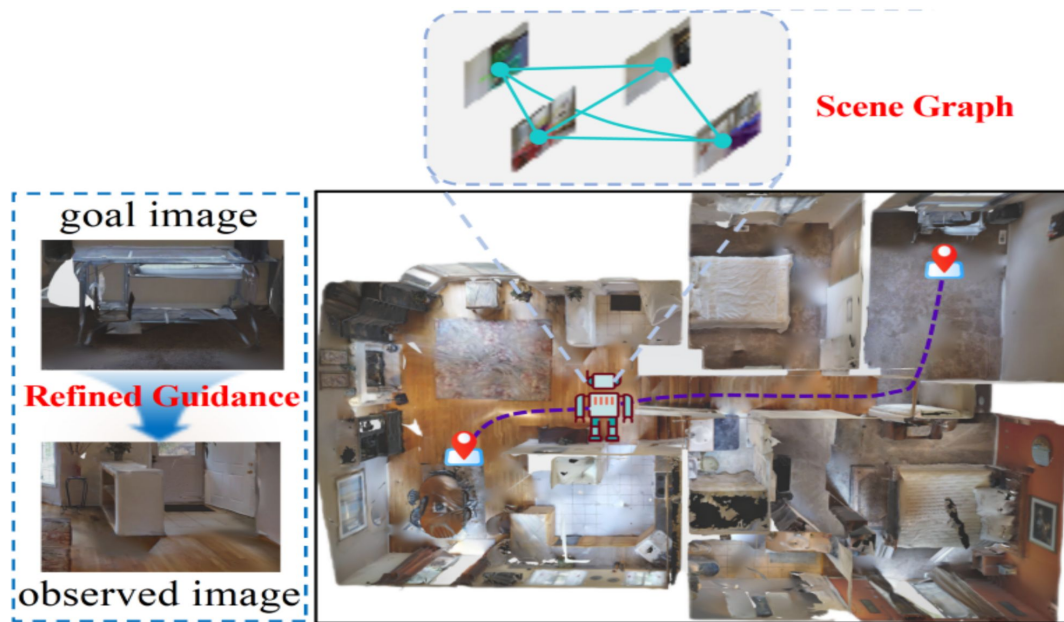
four core task categories:

- Image-goal navigation
- Embodied Question Answering (EQA)
- Vision-Language navigation (VLN)
- Object-goal navigation

Categorized by Goal Specification Modality

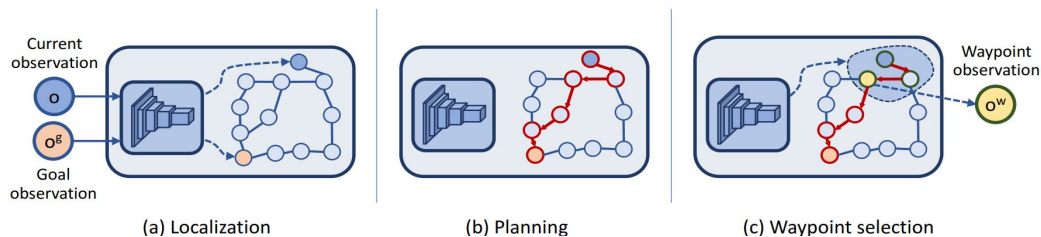
Image-goal Navigation

"Given an image of a target, an embodied agent must navigate in a 3D environment to reach that location."



A paradigm shift in navigation, aiming to search targets without precise positional information, but relying solely on a goal image.

Image-goal Navigation



TOPOLOGICAL MEMORY



(a) Maze



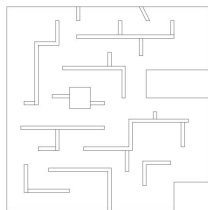
(b) Agent's observation



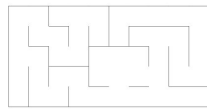
(c) Waypoint observation



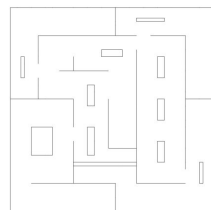
(d) Goal observation



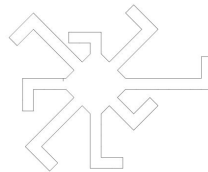
Train



Test-1



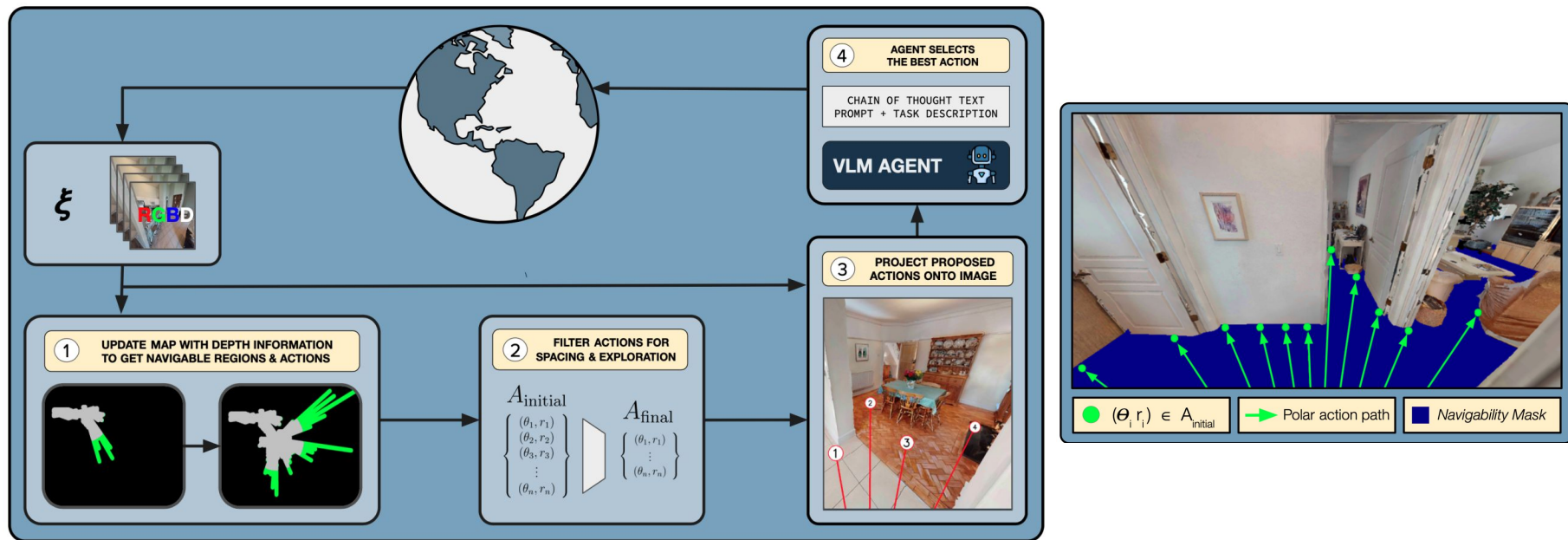
Test-2



Test-3

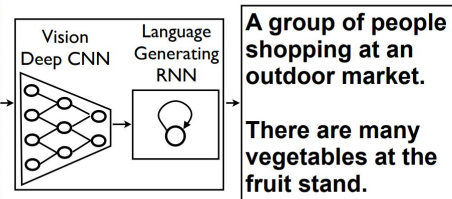
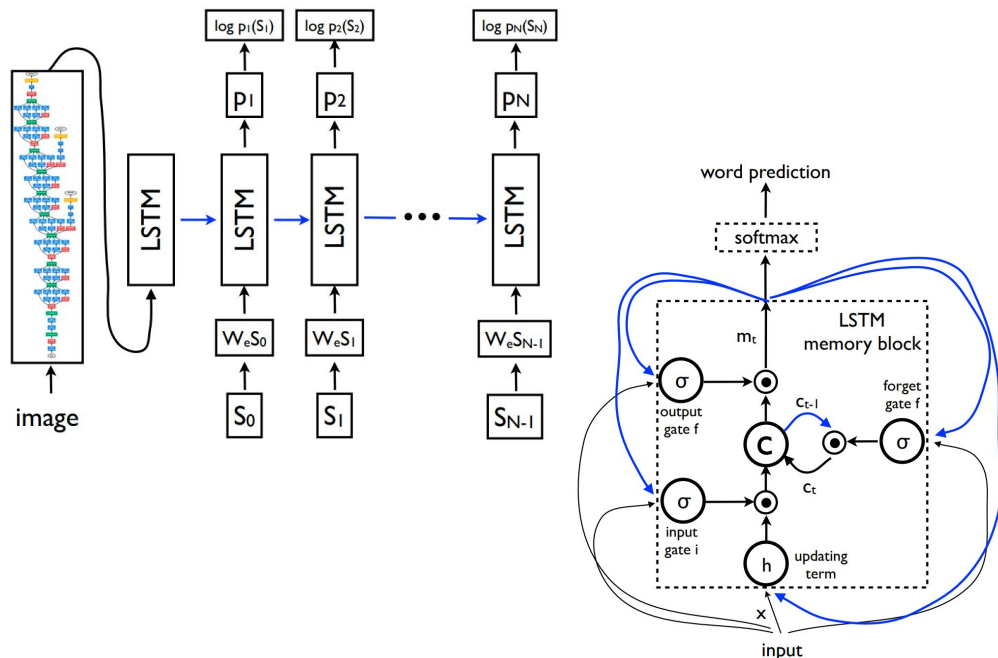
Image-goal Navigation

Apply **VLM** directly to action decision-making in embodied navigation.
Reformulate the navigation problem into image-based question answering.



Embodied Question Answering

"What color is the car parked next to the tree?"



It requires an embodied agent (usually a virtual or physical robot) to navigate and perceive within an environment in order to answer a question.

Embodied Question Answering



Human: Describe the video in detail.



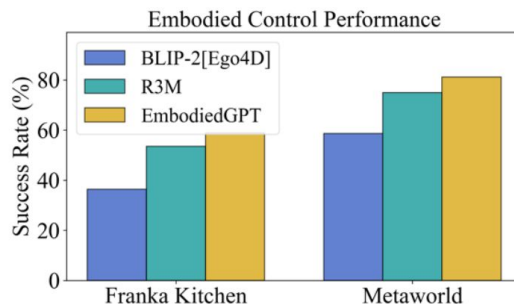
Assistant: In this video, a robot is engaged in a manipulation task in a kitchen environment. The scene features a white robotic arm, a black platform with four gray-white circles representing the heating elements of an induction cooktop. A white kettle with a handle can be seen in the bottom left corner of the platform, and a black microwave with a handle for opening sits on the left side of the platform. Two blue-gray cabinets are positioned above the platform, with the left cabinet having two doors with handles and the right cabinet featuring a sliding door with a handle. *The video captures the robotic arm in the process of opening the right cabinet's sliding door by first grabbing the handle and pulling it outwards.*



Human: Can you write a detailed plan for the task the robot is performing?

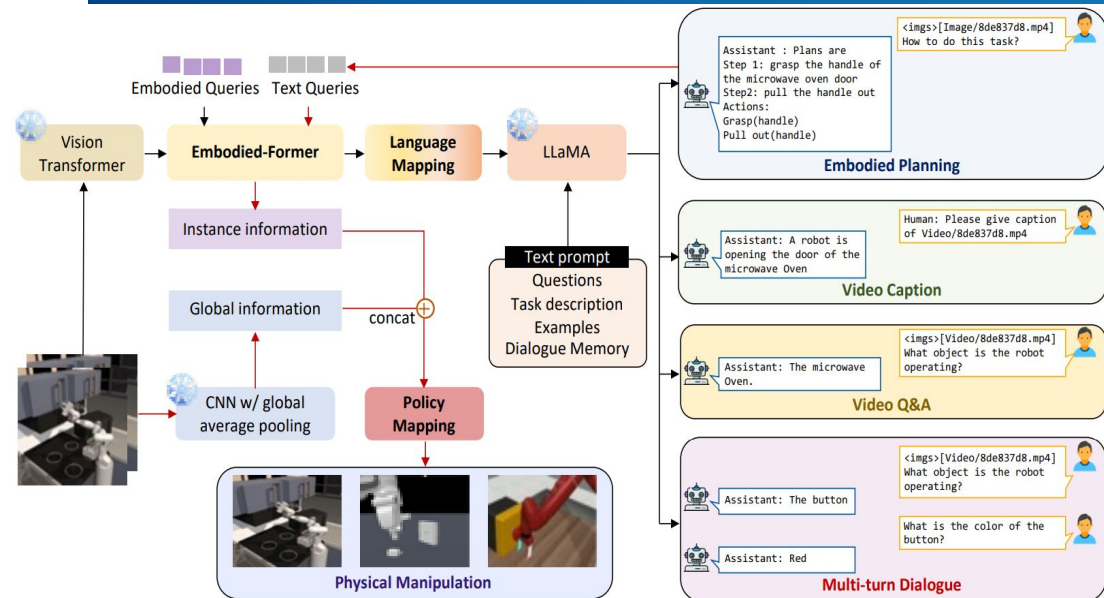


Assistant: The task is *opening the sliding door*.
Step 1: *Move to the left side* of the platform.
Step 2: *Grip the handle* on the right side of the door.
Step 3: *Pull it to the right*.
Step 4: *Hold the handle still* while the door slides open.
Step 5: *Release the handle* when the door is open.



EmbodiedGPT :
Through the training paradigm of "Embodied CoT", VLM learns to generate structured task plans from visual inputs and establishes a closed-loop system from high-level planning to low-level action execution.

Embodied Question Answering



Overall framework of EmbodiedGPT

Human: Give a detailed explanation of the image, describe the scene and the observed objects, and spatial relationships. Where should I go if I wish to find a coat hanger?

EmbodiedGPT:

1. The image depicts a doorway leading into a bedroom, with a clock hanging on the wall beside it and a picture of a woman further to the right.
2. There is a white closet suitable for storing clothes on the right side of the bedroom.
3. If one needs to hang a coat, the white closet on the left seem to be the logical choice.

Visual ChatGPT:

The image shows a bathroom with a clock on the wall and a toilet in the corner. The clock is white and has a black face with two hands. The walls are tiled and there is a window in the room.

The image shows a bathroom with a clock and a toilet. **There is no coat hanger visible in the image.**

Comparison between EmbodiedGPT and VisualGPT in the question-answering task

Evaluation on embodied control tasks

Model	Franka(10 demos)	Franka(25 demos)	Meta-World(10 demos)	Meta-World(25 demos)
EmbodiedGPT	50.8% ± 2.8	58.5% ± 2.7	76.4% ± 2.2	81.2% ± 2.0
- Close-loop	38.6% ± 2.9	47.3% ± 2.5	62.7% ± 2.2	64.9% ± 2.0
- COT	26.2% ± 3.2	36.4% ± 2.7	55.2% ± 2.4	58.7% ± 2.0

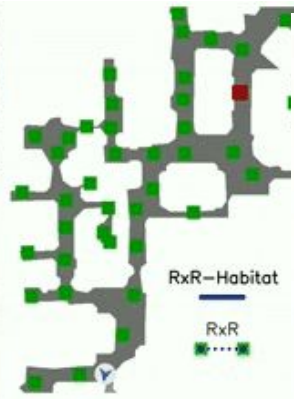
Table 2: Ablation on the closed-loop spans from planning to low-level control, and "chain-of-thought"

Model	Object(\uparrow)	Spatial(\uparrow)	Redundancy(\downarrow)	Plan Reasonable(\uparrow)	Plan Executable(\uparrow)
Minigt4	5.6	4.8	4.4	4.5	4.8
LLaVA-7B	7.3	7.4	3.9	7.5	6.6
LLaVA-13B	8.5	8.6	3.4	8.4	7.6
EmbodiedGPT	8.4	8.8	2.6	8.8	8.4

Table 1: Generate Quality Evaluation on image input tasks.

Vision-Language Navigation

"Given the egocentric image observation sequence with corresponding language instruction as input, following the text instruction and reach out to the target area."

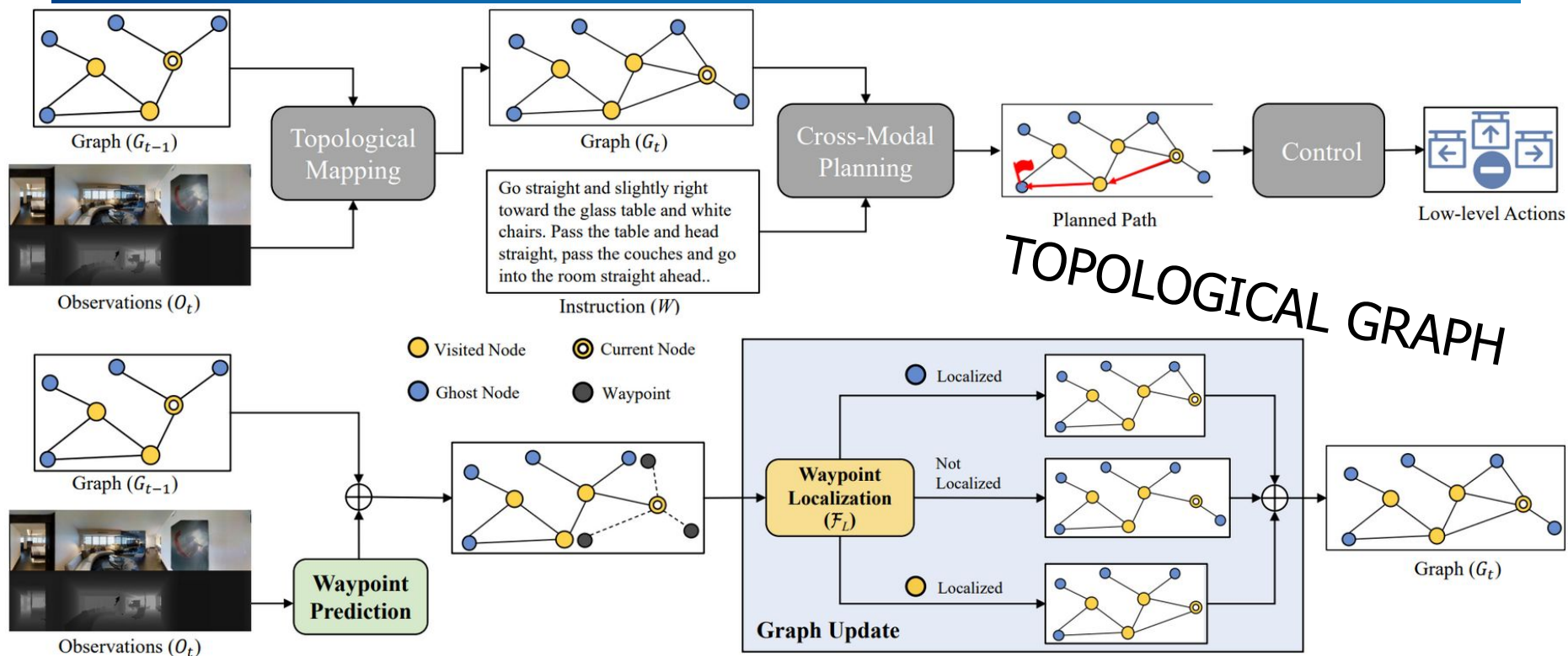


You are in a bedroom. Turn around to the left until you see a door leading out into a hallway, go through it. Hang a right and walk between the island and the couch on your left. When you are between the second and third chairs for the island stop.

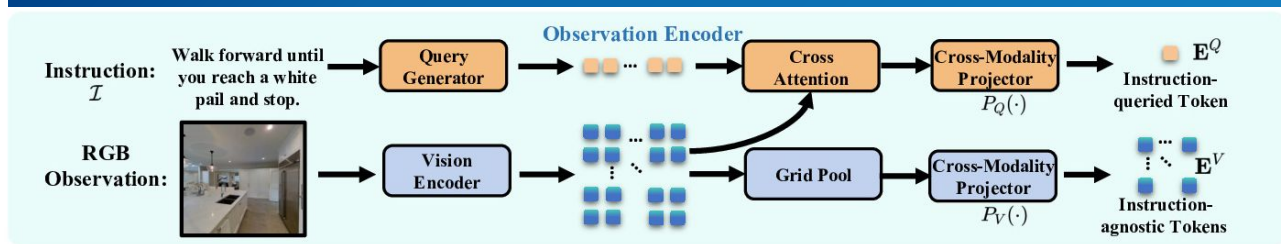
Leave the bedroom, and enter the kitchen. Walk forward, and take a left at the couch. Stop in front of the window.

— smooth VLN-CE path
— VLN nav-graph hops

Vision-Language Navigation

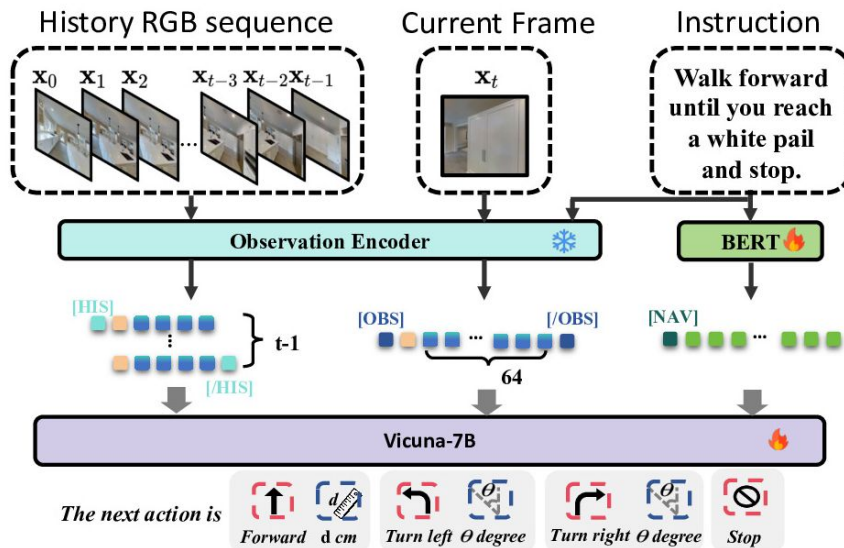
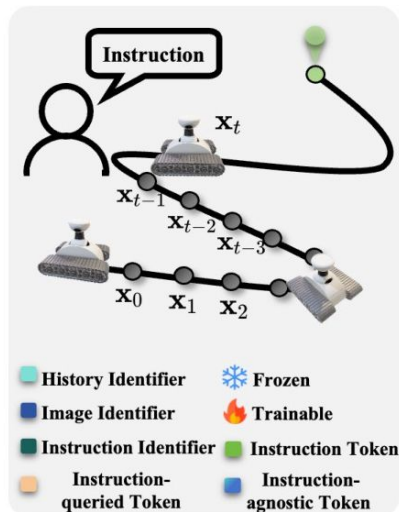


Vision-Language Navigation



Using only RGB video as input and directly output low-level actions from a video-based vision-language-model

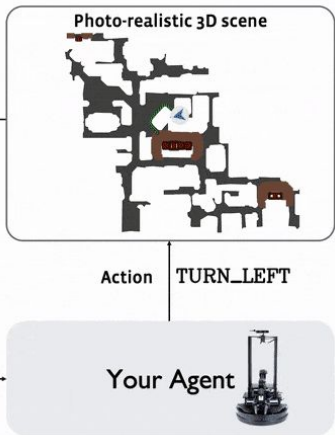
No need for translation, rotation, and depth information!



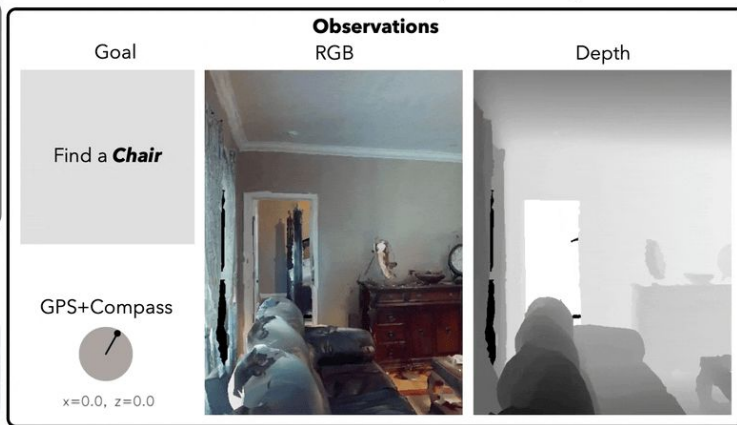
Object-goal Navigation

"Given an object category, the embodied agent must navigate to the specified object in unknown 3D environment."

Object Goal Nav Task:

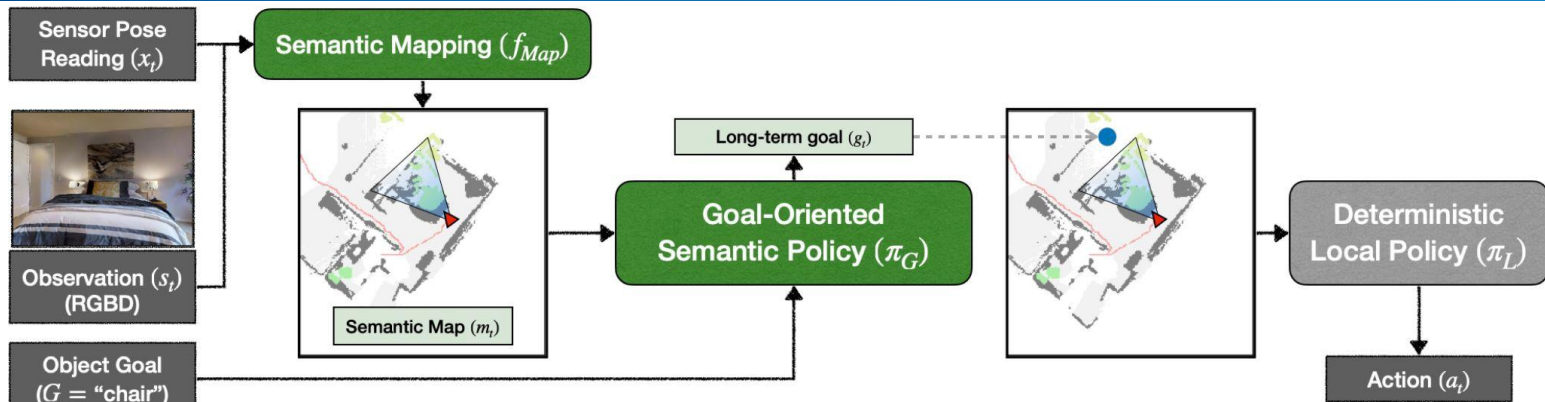


ObjectGoal Navigation Task



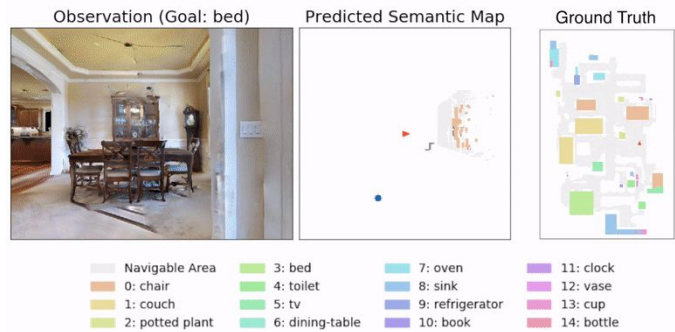
Find an instance of an object category ('find a chair') by navigating to it, no prior map information, only use its onboard sensory input to explore and navigate.

Object-goal Navigation

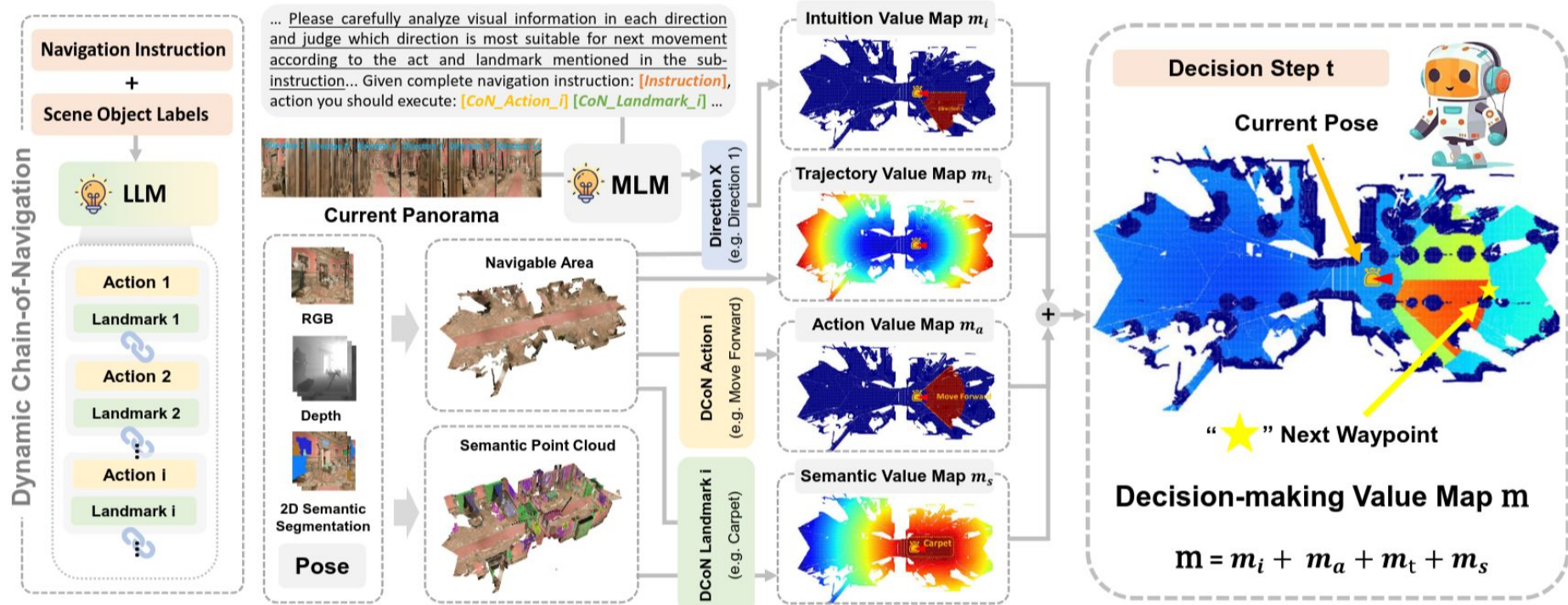


Semantic map-based Exploration

1. Lack of Zero-shot transfer ability
2. Limited categories of goal objects
3. Time-consuming training in Simulator
4. Sim-2-Real Gap



Object-goal Navigation



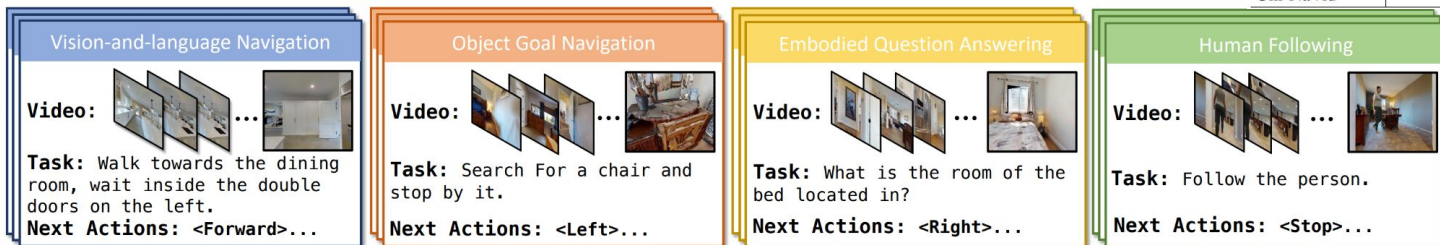
Using VLM to judge navigation directions, use LLM to plan Dynamic Chain-of-Navigation

Unified Frameworks for Embodied AI

PKU Uni-Navid : Unifying Embodied Navigation Tasks

Methods	Action D.E. C.E.	Embodied Navigation Tasks			
		VLN [44]	ObjNav [76]	EQA [90]	Follow [68]
VLMaps [34]	✓	✓	✓		
NaviLLM [114]	✓	✓	✓	✓	
InstructNav [61]	✓	✓	✓		
Poliformer [106]	✓		✓		✓
Uni-NaVid	✓	✓	✓	✓	✓

Training Data



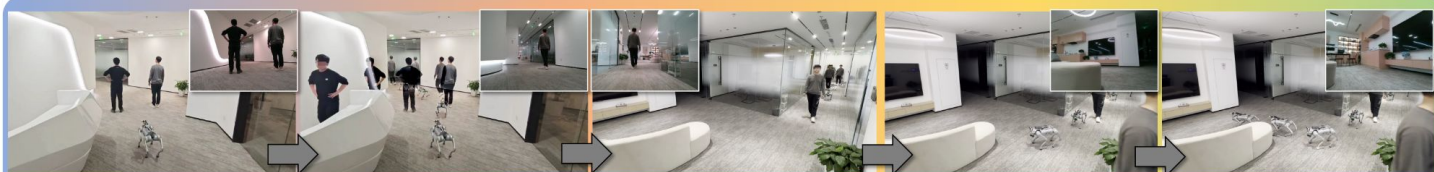
Uni-NaVid learns general navigation skills across **four** embodied navigation tasks.

3.6 Million Language Instruction
 Egocentric Video

Uni-NaVid



Zero-shot deployment



"Move to the man on the right side. Then follow that man until you see a sofa. Turn right and search for a TV, stop by the TV. Finally, what is the color of the sofa?" Uni-NaVid: Beige

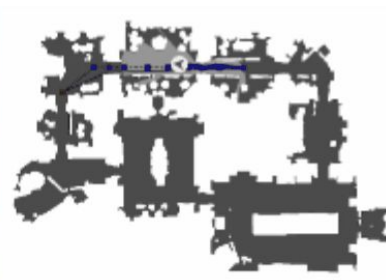
Unified Frameworks for Embodied AI

Compositional Navigation Task

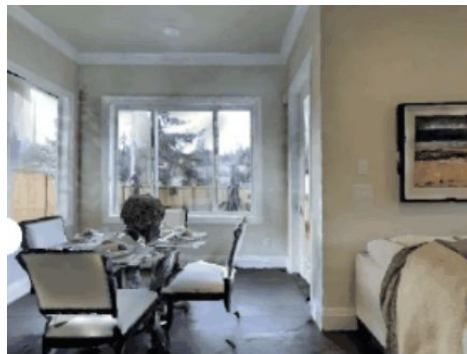
Move to the sofa, then turn left and search for a person, follow the person.



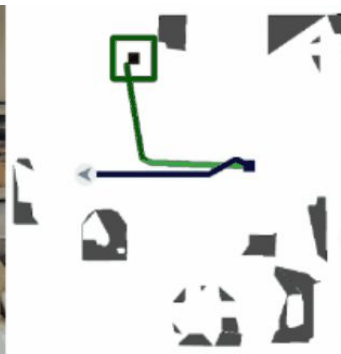
You are standing in a room, facing towards the fireplace and top of the fireplace there is a door, slightly turn right, in-front of you there is a open door, walk through the open door and exit the room, walk straight, in-front of you there is a open door, walk through the open door and enter the room, in-front of you you can see a desk, to the left you can see an open entrance, walk to the open entrance and stand in-front of it, look is your end point.
Pending action: forward



VLN Task



what room is the fireplace located in?
Pending action: forward



Embodied Question Answering Task

Conclusions

VLM enable the agent with super powerful temporal-spatial understanding ability. *"One ring to rule them all"* become possible. Using one VLM to unify all embodied navigation tasks will be the future research direction

Some good research directions for future research

1. Agent-Human-Interaction
2. Flying-wheel high-quality data augmentation
3. Cross-Floor and Long-Horizon inference

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Vision-Language Model for embodied navigation

Thank you.

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Quiz

Quiz 1.

Visual-Language Models (VLMs) enable robots to jointly understand natural language instructions and visual scenes, thereby enhancing navigation tasks (True or False).

Quiz 2.

In VLMs-based Vision-Language-Navigation, the agent needs pose and depth information for training and inference (True or False)