

LLaMAR: Long-Horizon Planning for Multi-Agent Robots in Partially Observable Environments

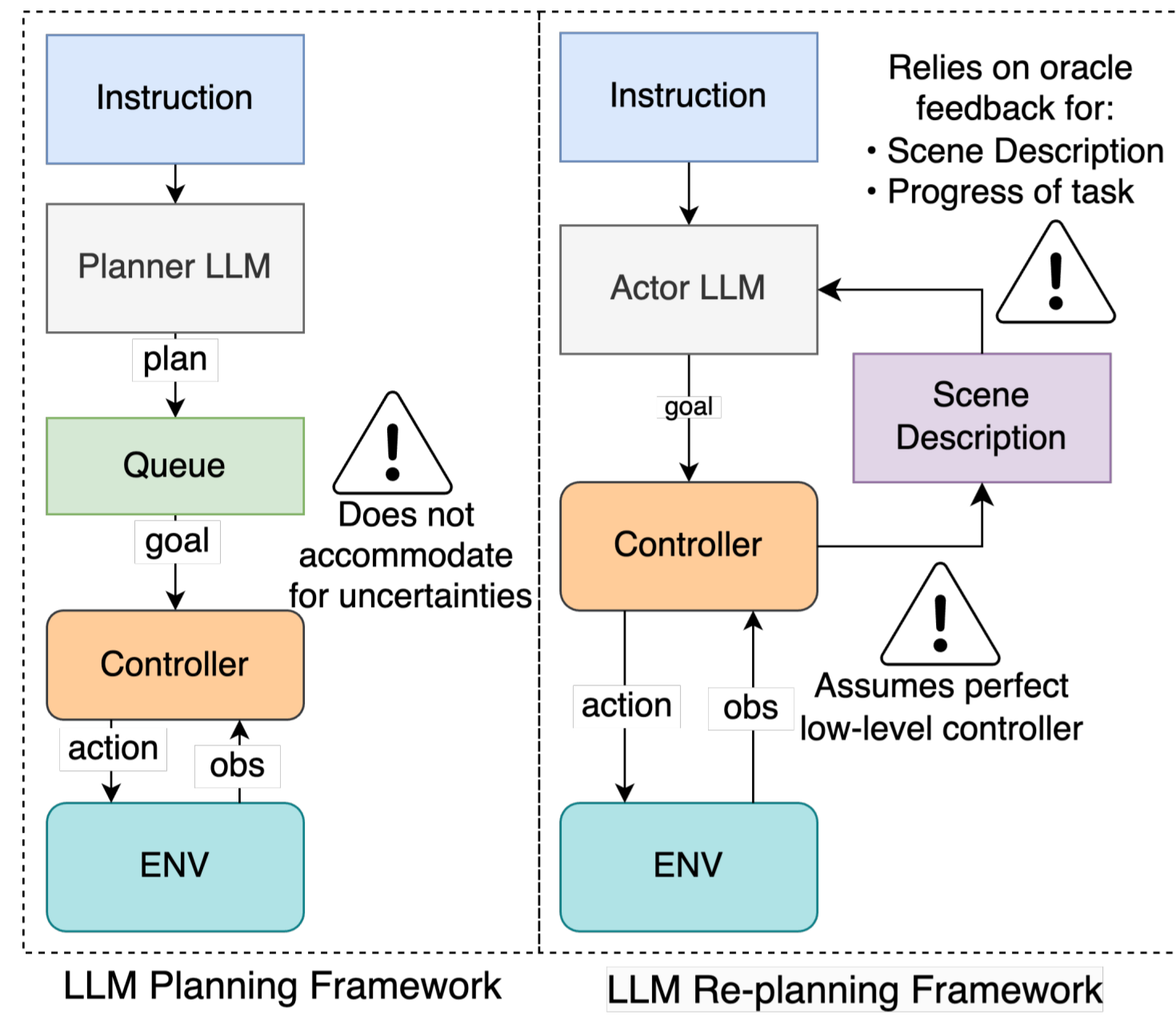
Siddharth Nayak^{* 1} Adelmo Orozco^{* 1} Marina Ten Have¹ Vittal Thirumalai¹ Jackson Zhang¹ Darren Chen¹ Aditya Kapoor²
 Eric Robinson³ Karthik Gopalakrishnan⁴ James Harrison⁵ Brian Ichter⁵ Anuj Mahajan⁶ Hamsa Balakrishnan¹

¹Massachusetts Institute of Technology ²TCS RnI ³USAF-MIT AI Accelerator ⁴Stanford University ⁵Google DeepMind ⁶Apple



Planning with LLMs

Current Approaches to Planning with LLMs



	Two Step	Smart LLM	S-ATLAS	CoELA	LLaMAR
Dynamic Planning	X	X	✓	✓	✓
Local Information	X	X	X	✓	✓
Failure Correction	X	X	X	X	✓
Self Verification	X	X	X	X	✓

Table 1. Comparison of planning methods and their capabilities.

Need a method that can accommodate uncertainties, and does not rely on perfect low-level control and oracle feedback.

Results

LLaMAR vs Baseline Performance

Algorithm	LM	SR↑	TR↑	C↑	B↑
Act	GPT-4V	0.33	0.67	0.91	0.59
ReAct	GPT-4V	0.34	0.72	0.92	0.67
CoT	GPT-4V	0.14	0.59	0.87	0.62
SmartLLM	GPT-4V	0.11	0.23	0.91	0.45
CoELA	GPT-4V	0.25	0.46	0.76	0.73
LLaMAR	GPT-4	0.51	0.85	0.95	0.83
LLaMAR	LLaVA	0.54	0.84	0.91	0.75
LLaMAR	IDEFICS-2	0.57	0.86	0.94	0.78
LLaMAR	CogVLM	0.61	0.89	0.95	0.80
LLaMAR (w/o expl)	GPT-4V	0.62	0.87	0.95	0.82
LLaMAR (w/ expl)	GPT-4V	0.66	0.91	0.97	0.82

Table 2. Comparison of LLaMAR against baselines averaged across all tasks.

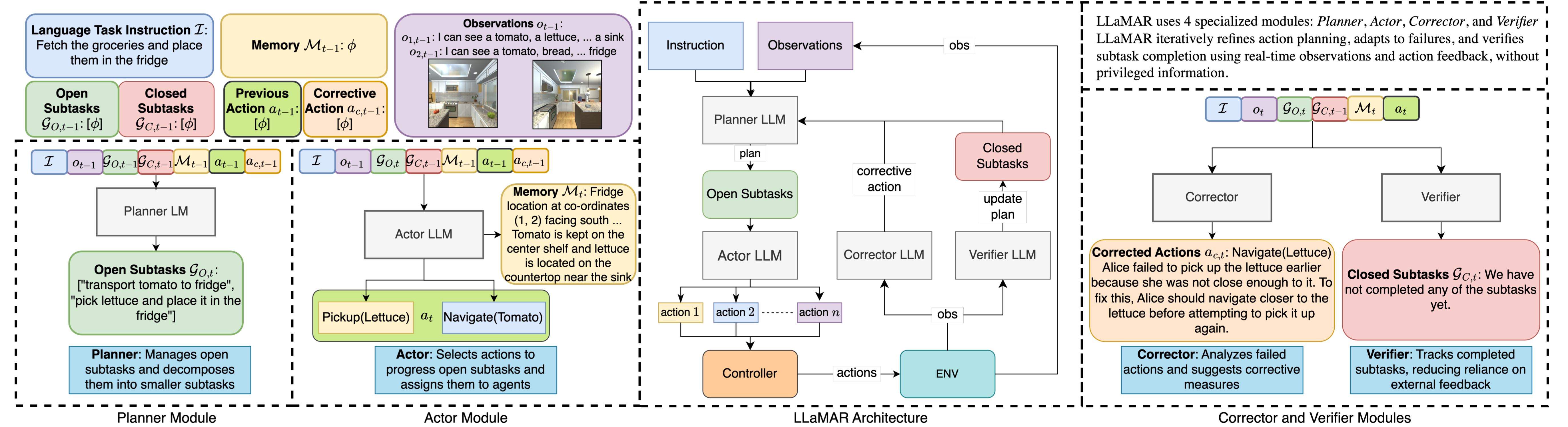
Partitioning the planning process into distinct modules enhances performance in MAP-THOR

Modules Used	SR ↑	TR ↑	C ↑	B ↑
Actor	0.33	0.67	0.91	0.59
Planner + Actor + Verifier	0.45	0.78	0.92	0.69
Planner + Actor + Corrector†	0.67	0.91	0.97	0.84
Planner + Actor + Corrector + Verifier +	0.66	0.91	0.97	0.82

Table 3. Performance in the 2-agent scenarios in MAP-THOR obtained by ablating different modules in LLaMAR

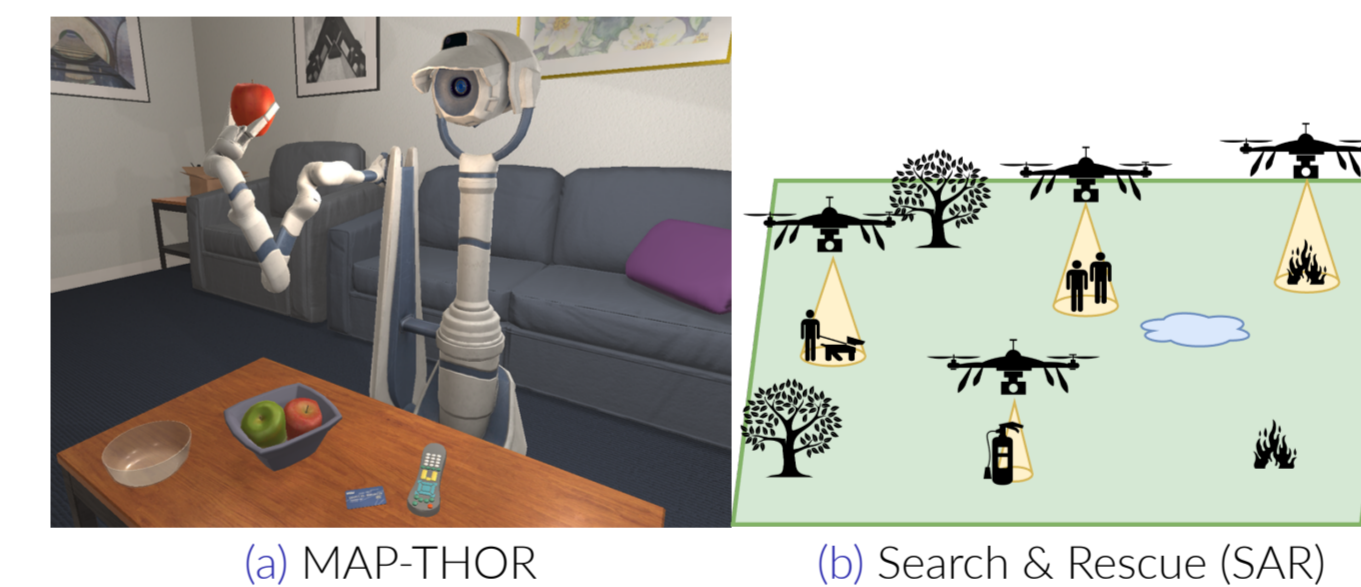
LLaMAR is able to perform as well as a model with an oracle-based verifier

LLaMAR Architecture



Task Environments

- MAP-THOR:** A test-suite and benchmark on language-based multi-agent robotic planning based on AI2THOR.
- Search & Rescue (SAR):** Agents are tasked with extinguishing fires before they spread and rescuing missing humans.
- LLaMAR:** Creates performant long-horizon planning in multi-agent tasks by generating subtasks and assigning them to different agents.



We perform experiments in two different multi-agent robotics environments.

Conclusions

- LLaMAR creates long-horizon plans in multi-agent tasks by creating and assigning subtasks to different agents.
- LLaMAR enables performant multi-agent planning in uncertain environments.
- We introduce MAP-THOR a benchmark dataset consisting of language-conditioned multi-agent robotic tasks with various difficulty levels.

Results

# of agents	MAP-THOR			SAR		
	SR↑	TR↑	C↑	SR↑	TR↑	C↑
1	0.37	0.67	0.87	0.28	0.75	0.86
2	0.62	0.87	0.95	0.44	0.86	0.94
3	0.70	0.91	0.98	0.68	0.92	0.96
4	0.68	0.90	0.99	0.72	0.94	0.98
5	0.62	0.90	0.99	0.74	0.96	1.00

Table 4. LLaMAR with various number of agents in the scenario in both MAP-THOR and SAR environments

Increasing number of agents improves performance in SAR

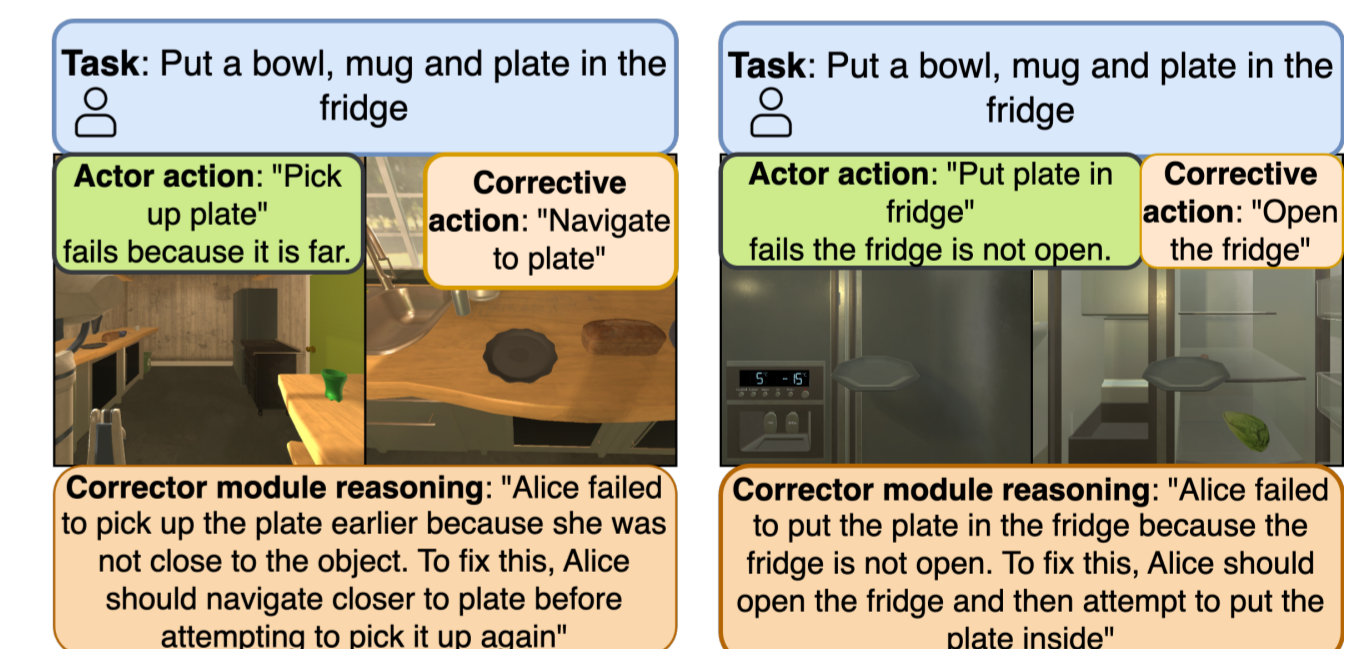


Figure 1. Failure Correction with visual feedback

Corrector helps with reasoning on failures at low-level execution

Limitations & Assumptions

- Low-level controllers can perform language-conditioned actions. e.g., Pickup(Bowl)
- When an agent observes an object, its location is inherently stored in the navigation module's memory.
- Performance is limited by the underlying VLM and hence has limited spatial reasoning
- LLaMAR incurs a higher computational cost at each step due to the involvement of multiple language models during each iteration.
- The experiments are conducted in a simulated environment rather than in the real world.