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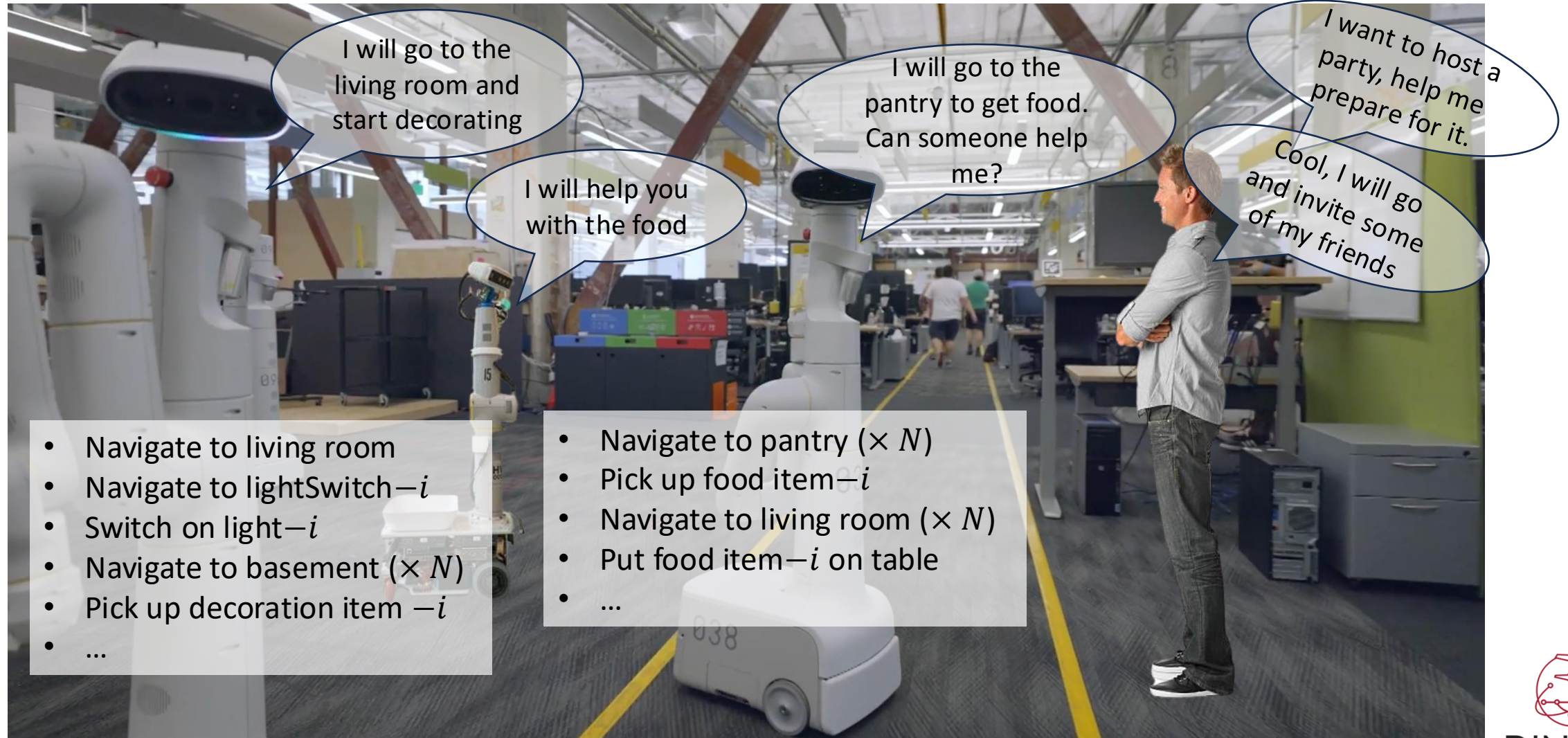
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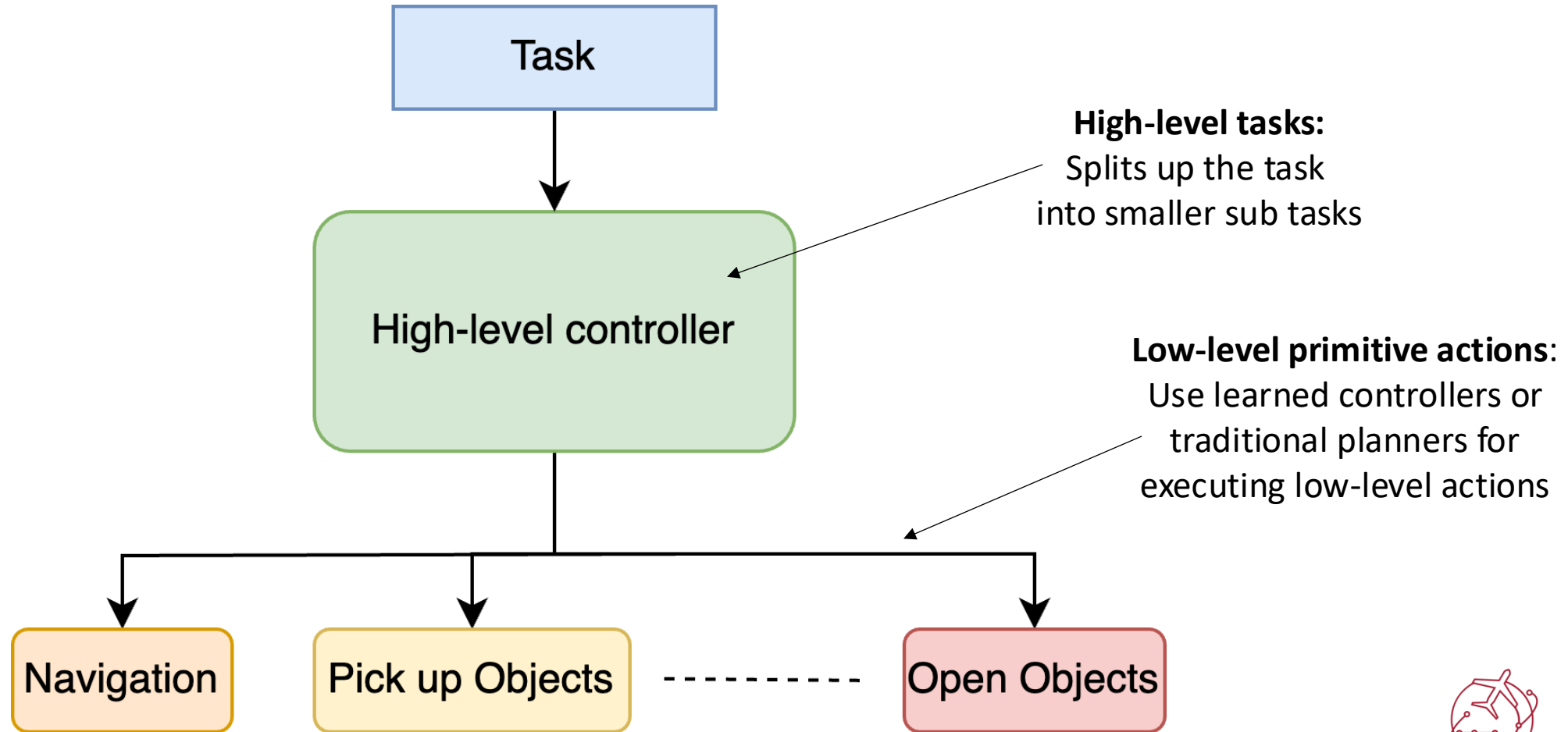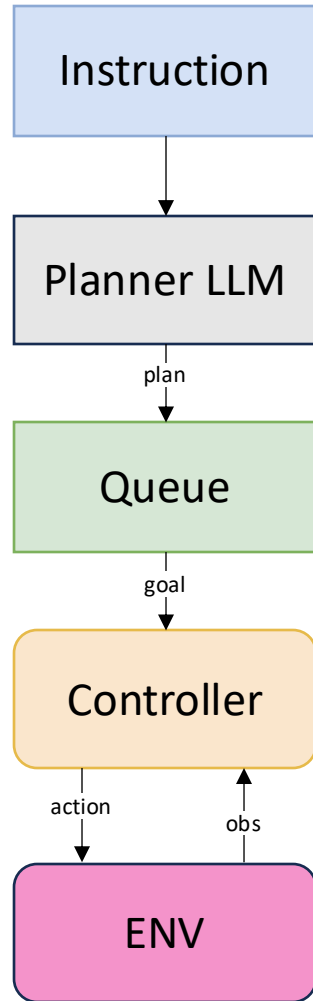
Motivation

Long-Horizon Planning

Hierarchical Planning

Task

High-level tasks:
Splits up the task
into smaller sub tasks

High-level controller

Low-level primitive actions:
Use learned controllers or
traditional planners for
executing low-level actions

Navigation   Pick up Objects - - - - - - - - - Open Objects

DINaMo

LLMs for planning

Instruction

Planner LLM

plan

Queue

goal

Controller

action | obs

ENV

- Does not accommodate for uncertainties
- Requires prior knowledge about subtasks (global information)

Time	Event
09:00	Breakfast 09:00 – 09:45
	Paper Writing 09:45 – 11:30
	Meeting 1 11:30 – 12:30
	Lunch 12:30 – 13:30
	Brainstorming with John 13:30 – 15:30
	Paper Review 15:30 – 17:00
	Tennis 17:00 – 18:00
	Dinner Preparation 18:00 – 18:45
	Dinner 18:45 – 19:30
	Household Chores 19:30 – 20:30
	Guitar Practice 20:30 – 21:30

DINaMo

LLMs for Reactive Planning
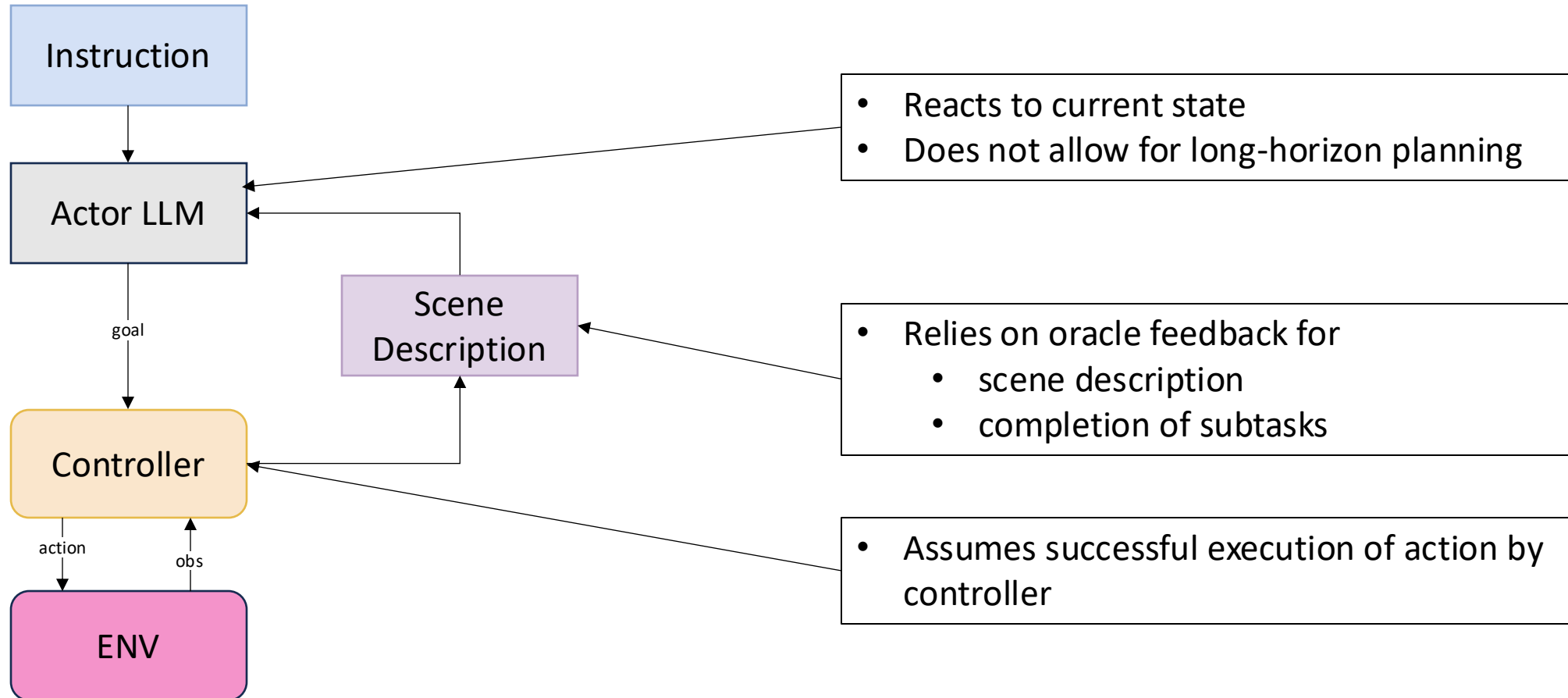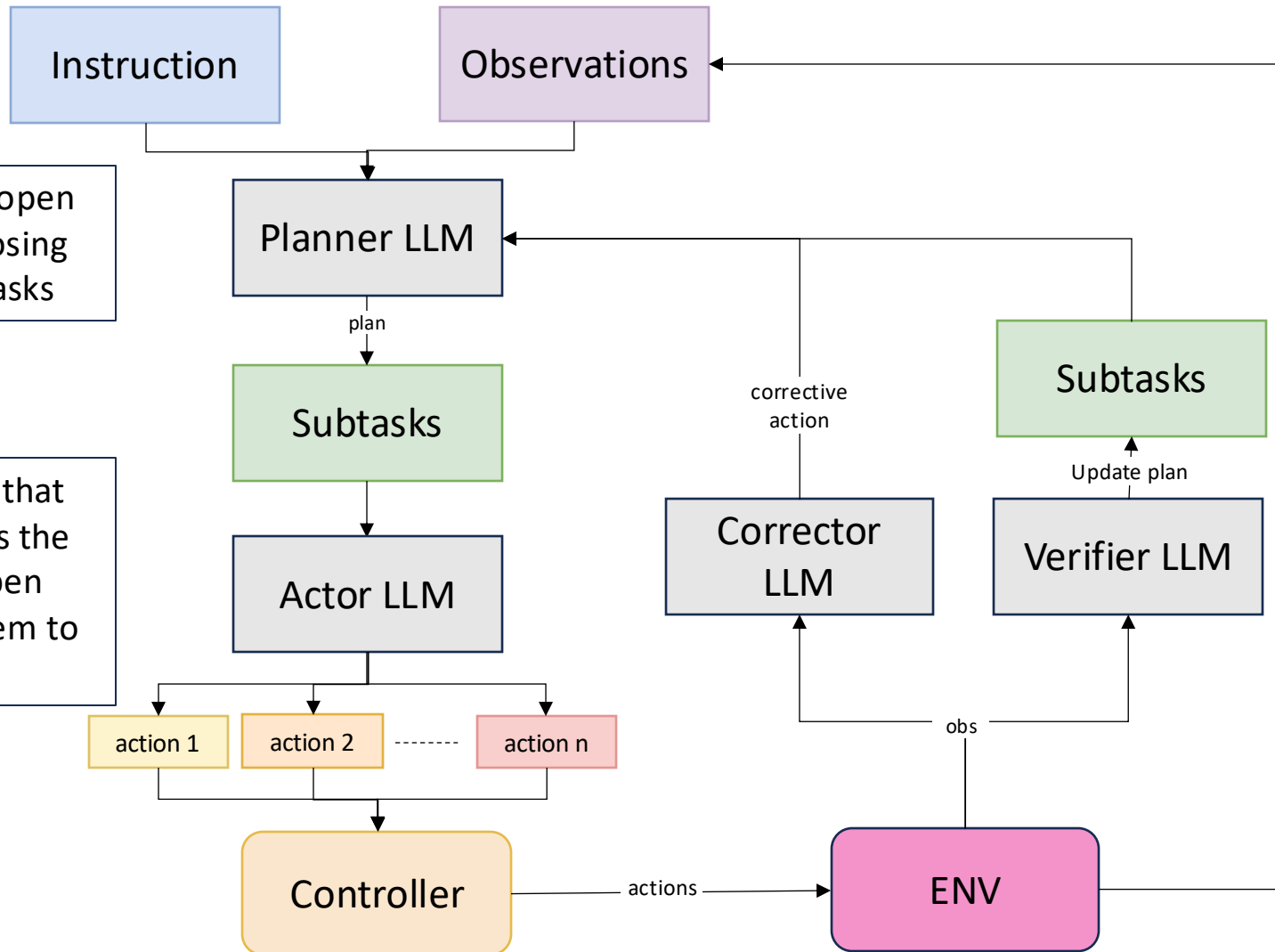
Instruction

Actor LLM

goal

Controller

action   obs

ENV

Scene Description

- Reacts to current state
- Does not allow for long-horizon planning

- Relies on oracle feedback for
  - scene description
  - completion of subtasks

- Assumes successful execution of action by controller

LLaMAR

MAP-THOR

45 tasks
each with 5 seeds

Tasks

Metrics

Benchmark

Categorized
based on
difficulty of tasks

Explicit item type, quantity and target
E.g., Put bread, lettuce, tomato in the fridge

Explicit item type and target, implicit quantity
E.g., Put all the apples in the fridge

Explicit target, implicit item type and quantity
E.g., Put all groceries in the fridge

Implicit item type, quantity and target
E.g., Clear the floor by placing the
items at their appropriate positions

DINaMo

Demo

Human Instruction: "I want to put the groceries in the fridge

Alice's POV

Bob's POV

Key Takeaways

- LLaMAR performs 30% better than other LLM-based methods for multi-agent long-horizon planning

- Vision Language Models perform better than pure text-based language models

- A **modular cognitive architecture** with distinct roles helps with solving complex tasks.

Key Contributions:

- A **modular cognitive architecture** called LLaMAR which integrates planning, acting, correcting and self-verification through distinct LLM roles

- MAP-THOR a **test-suite and a benchmark** on language-based multi-agent robotic planning based on AI2THOR

- LLaMAR can create **performant long-horizon planning** in multi-agent tasks by creating subtasks and assigning them to different agents

DINaMo