Institut de Robòtica i Informàtica Industrial

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UNIVERSITAT POLITÈCNICA DE CATALUNYA BARCELONATECH

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Flexible Plan Generation, Adaptation and Execution in Human-Robot Collaboration

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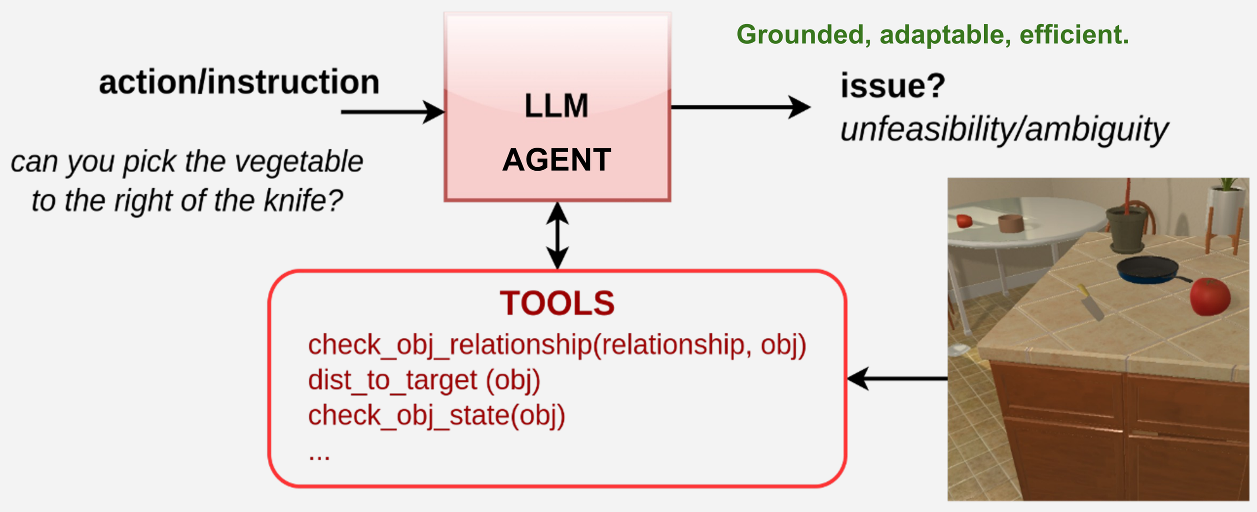
HOW CAN WE PREVENT AND EXPLAIN ACTION EXECUTION ISSUES?

Objective: Detect and explain issues encountered before executing actions/instructions in an adaptive and efficient manner.



How? LLM agent: LLM equipped with grounded perception tools, for selective information gathering through reasoning and tool calls.

- ✅ No need to define specific preconditions or rules – applicable and adaptable to unseen actions and arguments. Checks are simply limited by tool capabilities.
- ✅ No need to define full scene graph: focus on important information only.

```
USER: pick the vegetable on the right of the knife
FROM ENVIRONMENT: The objects in front of the robot are: grounded object list = ['Drawer1',
'Drawer2', 'Cabinet1', 'Drawer3', 'Cabinet2', 'Cabinet3', 'Drawer4', 'DiningTable',
'Cabinet4', 'Tomato', 'Knife', 'Bowl', 'HousePlant1', 'Plate', 'Pan', 'ButterKnife',
'HousePlant2', 'Chair1', 'Chair2', 'CounterTop']. The robot is holding None
AGENT: 1. Object Grounding:
- **Knife**: Clearly identified in the object list.
- **Vegetable**: Needs to be identified as a specific object. The only vegetable in the list
is **Tomato**.
2. Question Generation:
  1. Is the Tomato on the right of the Knife?
  2. Is there anything blocking the Tomato from being picked up?
  3. Is the Tomato within the robot's reach?
3. Tool Calls - Information Gathering:
call_tool{tool: check_obj_relationship, args: on the right of, Knife}
call_tool{tool: check_obj_relationship, args: blocking, Tomato}
call_tool{tool: dist_to_target, args: Tomato}
```

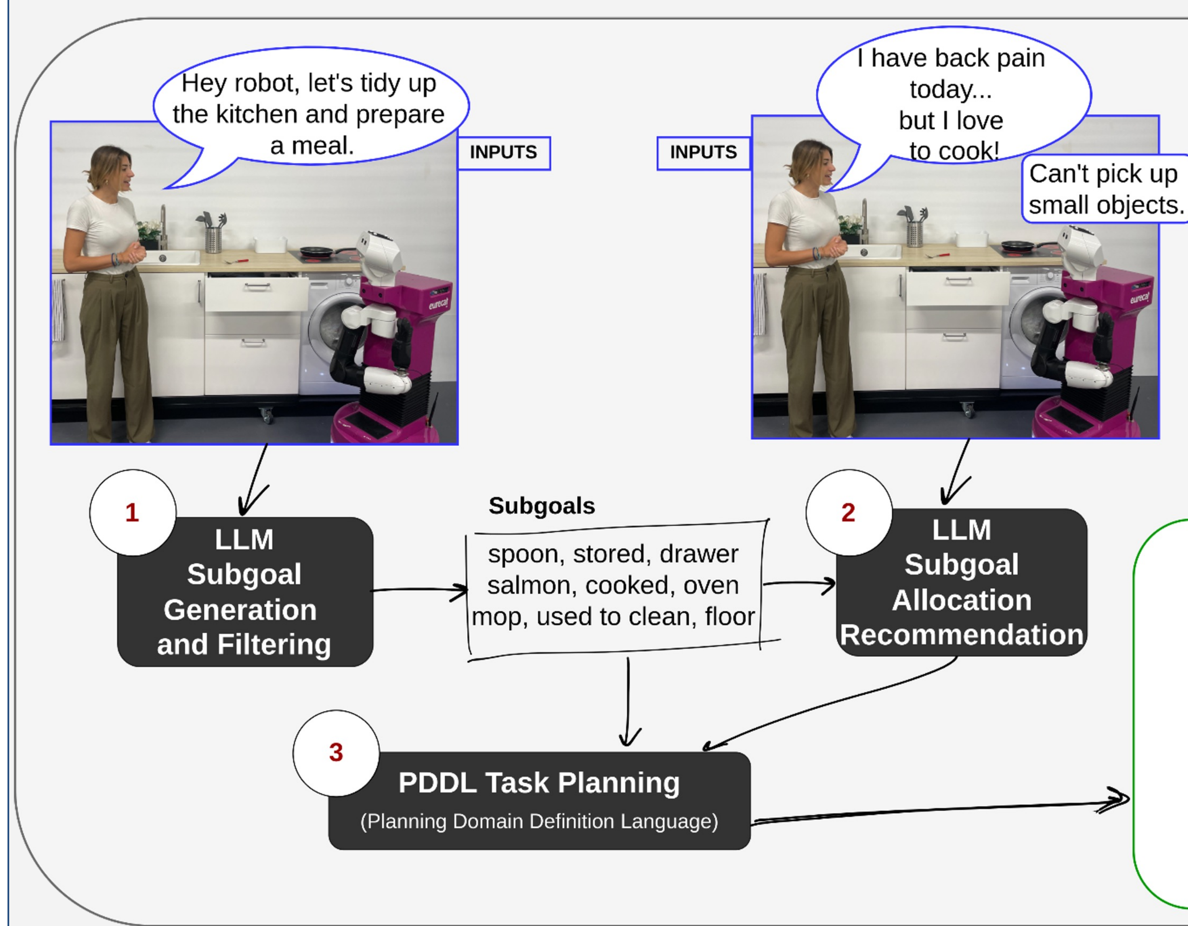
TOOL RESPONSES


```
AGENT: 4. Decision Making:
- The Tomato is confirmed to be on the right of the Knife.
- There is nothing blocking the Tomato from being picked up.
- The Tomato is 1.42m away, which is beyond the robot's 1.10m reach.

{"final_response": "unfeasibility", "explanation": "The Tomato is beyond the robot's reach
of 1.10m."}
```

HOW CAN WE GENERATE PLANS FROM NATURAL LANGUAGE ABSTRACT GOALS AND AGENT CONDITIONS? [4]

Objective: Generate grounded collaborative plans from a high level goal, with an appropriate action allocation influenced by agent conditions expressed in natural language.

How? Combination of LLMs and AI task planning - LLMs to generate subgoals from a high level goal and to influence their allocation based on agent conditions. Information translated into a grounded PDDL task planning problem.



- ✅ **LLMs** as **translators** between **Natural Language (NL) information** and a **structured AI task planning** problem.
- ✅ **Automated** and **flexible generation** of **Human-Robot Collaborative plans** from NL abstract goals and agent conditions.
- ✅ **Eliminated need** for **manual and laborious definition** of restricted **planning problems** and **agent models**.

PDDL problem

Planning Domain Definition Language

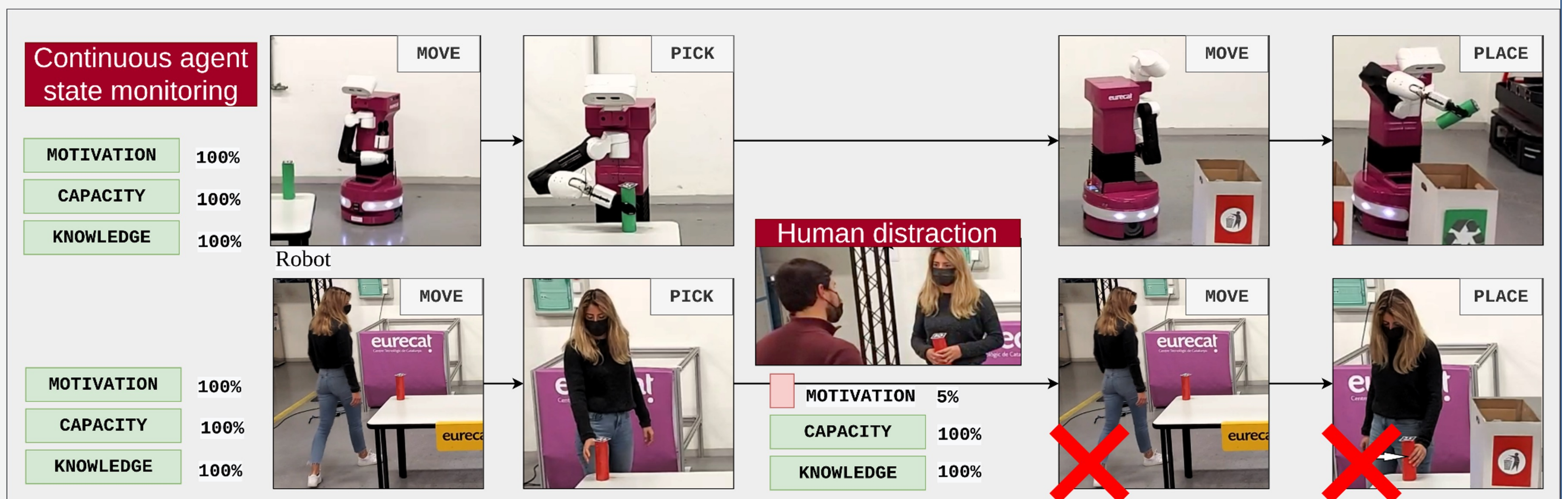
```
(:objects
     human robot – agent
     ; ... - obj ; from environment
     ; ... - loc ; from environment
)
(:init
     (agent_not_busy robot)(agent_not_busy human)…
     (= (total-cost) 0)

     ; action costs from LLM recommendations based on agent states
and preferences
     (stored_cost robot spoon drawer 100) ; etc.
)
(:goal (and
     ; goals from LLM based on environment
     (stored spoon drawer) ; etc.
)
(:metric minimize (+ (* 1 (total-cost))(* 1 (total-time)))) )
```

HOW CAN WE ADAPT THE PLAN TO THE AGENT'S STATES, AVOIDING FAILURES? [1]

Objective: Prevent failures in HRC plans by adapting the plan based on agent's states.

How? Integration of an agent model into action costs of the PDDL planning domain definition.

✅ Automated adaptation of plans to varying agent states.



The distraction is detected and reflected in the **agent model**, **integrated** in turn **as action costs into the planning definition. An action with a high cost for an agent will not be assigned to this agent:** a feasible plan with no failures replaces the original plan.

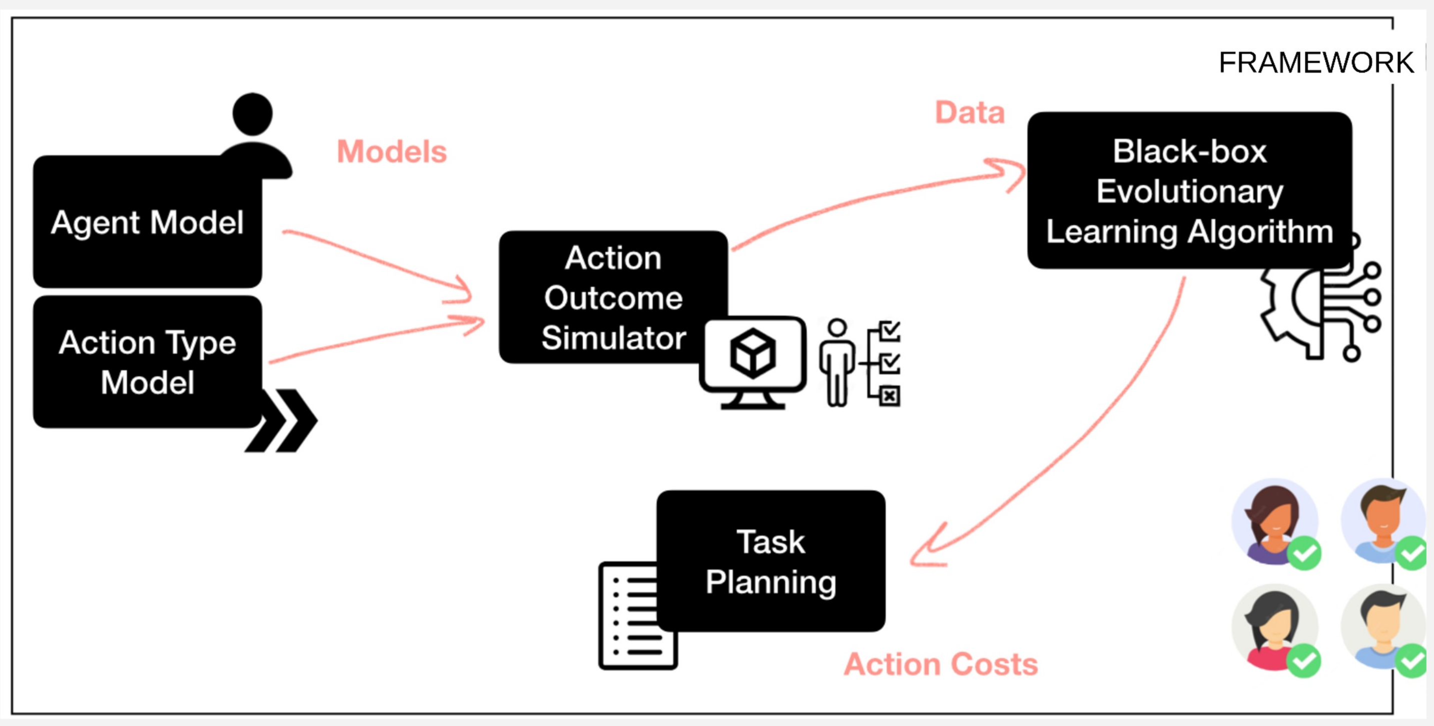
Replan: actions are reassigned to the robot, based on the new agent costs

HOW CAN WE LEARN APPROPRIATE ACTION COSTS FOR AN AGENT TYPE? [3]

Objective: Learn appropriate action cost values associated to different agent types, so that plans with a suitable action allocation adapted to these states can be generated.

How? Evolutionary algorithm for learning, where the black-box function consists of an action outcome simulator based on an agent and and an action type model.

✅ Provides an initial set of action costs, facilitating and accelerating posterior fine-tuning of action costs in real scenarios, where data collection is challenging.



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Research stays

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Publications

[1] Izquierdo-Badiola, S., Canal, G., Rizzo, C., Alenyà, G., (2022). Improved Task Planning through Failure Anticipation in Human-Robot Collaboration. In *IEEE International Conference on Robotics and Automation (ICRA).*

[2] Izquierdo-Badiola, S., Rizzo, C., Alenyà, G., (2022). Planning Interactions as an Event Handling Solution for Successful and Balanced Human-Robot Collaboration. In *Workshop IEEE International Conference on Intelligent Robots and Systems (IROS Workshop).*

[3] Izquierdo-Badiola, S., Alenyà, G., Rizzo, C. (2023). Adaptive Human-Robot Collaboration: Evolutionary Learning of Action Costs Using an Action Outcome Simulator. In *IEEE International Conference on Robot and Human Interactive Communication (RO-MAN).*

[4] Izquierdo-Badiola, S., Canal, G., Rizzo, C., Alenyà, G., (2024). PlanCollabNL: Leveraging Large Language Models for Adaptive Plan Generation in Human-Robot Collaboration. In *IEEE International Conference on Robotics and Automation (ICRA).*

[5] Izquierdo-Badiola, S., Canal, G., Coles, A., (2024). Planning for Human-Robot Collaboration Scenarios with Heterogeneous Costs and Durations In *European Conference on Artificial Intelligence (ECAI).*