Qualitative Causal Models for Self-Learning Autonomous Robots

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In one sentence:

A generic architecture, for embodied AI, inspired by how humans learn, using a qualitative causal world model and a planning algorithm providing reasoning and explainability for executing tasks.

Abstract:

Embodied agents learn qualitative causal world models as the basis for a cognitive architecture for autonomous agents and use them for control and planning. A qualitative model is learned that:

- captures the relations among the variables
- the contextual dependencies
- the qualitative influences.

Assuming:

- determinism
- monotonicity

We develop an integrated approach for:

- Learning the world model
- high level planning } Focus of this work
- low level control

The goal is for agents to incrementally learn to control their environment and perform tasks.

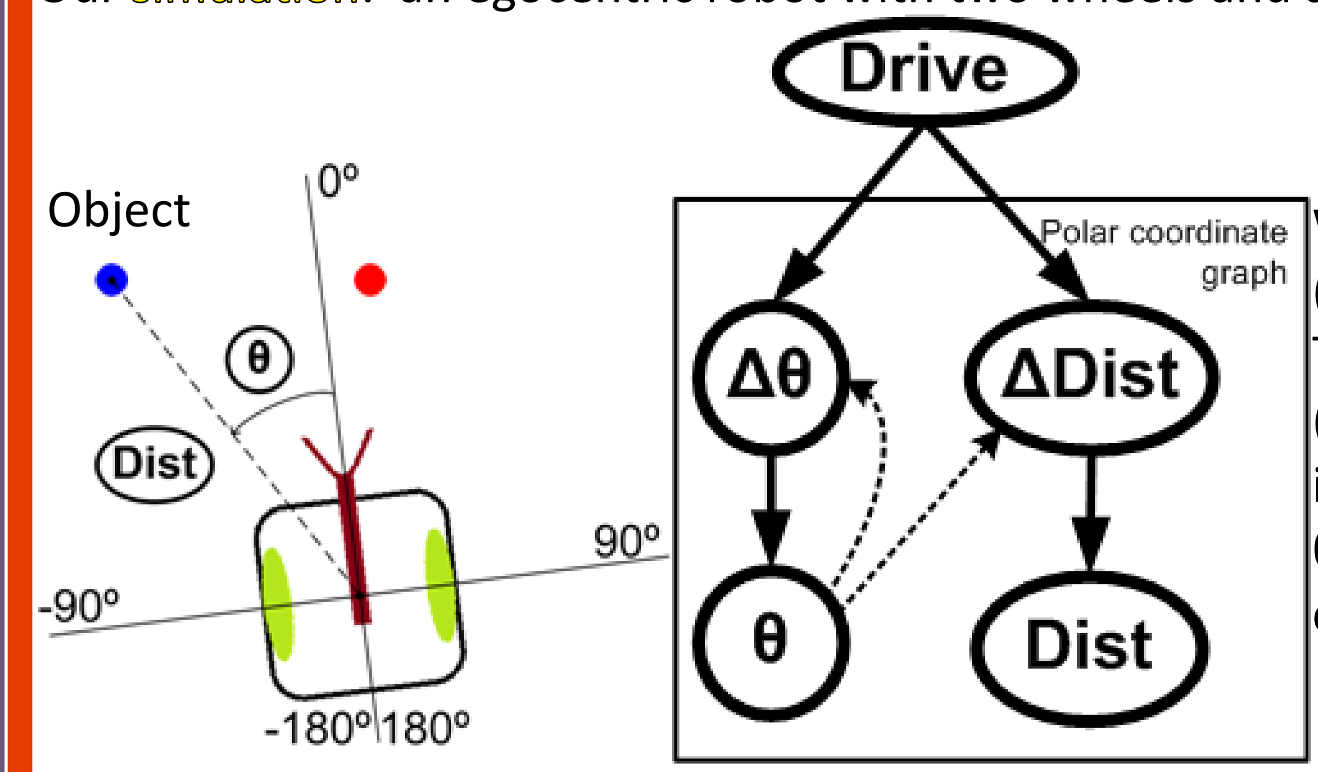
Advantages of learning qualitative models compared to the state-of-the-art RL:

- needing fewer data
- more generic
- provide explainability.

This work can be linked to symbolic top-down approaches, while our approach is bottom-up learning. It's the missing link between high-level symbolic representation of the world (like PDDL) and low-level control.

Qualitative model?

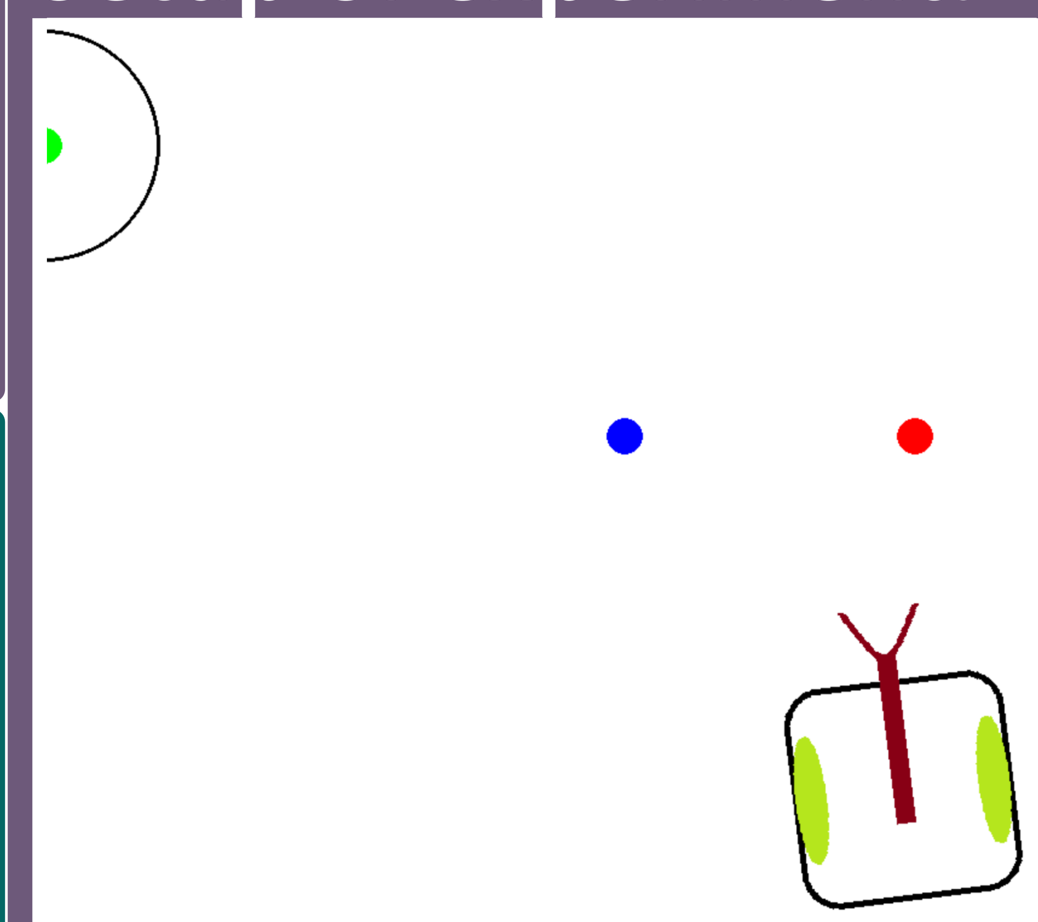
Our simulation: an egocentric robot with two wheels and a gripper



When Drive = + (move forward) Then ΔDist = - (decrease in distance) if (orientation) θ ∈ [-90,90] context

Egocentric robot with a blue object (left) and the graphical representation of the egocentric causal model between the robot's actions and an object, expressed in polar coordinates. (right)

Setup of experiment:



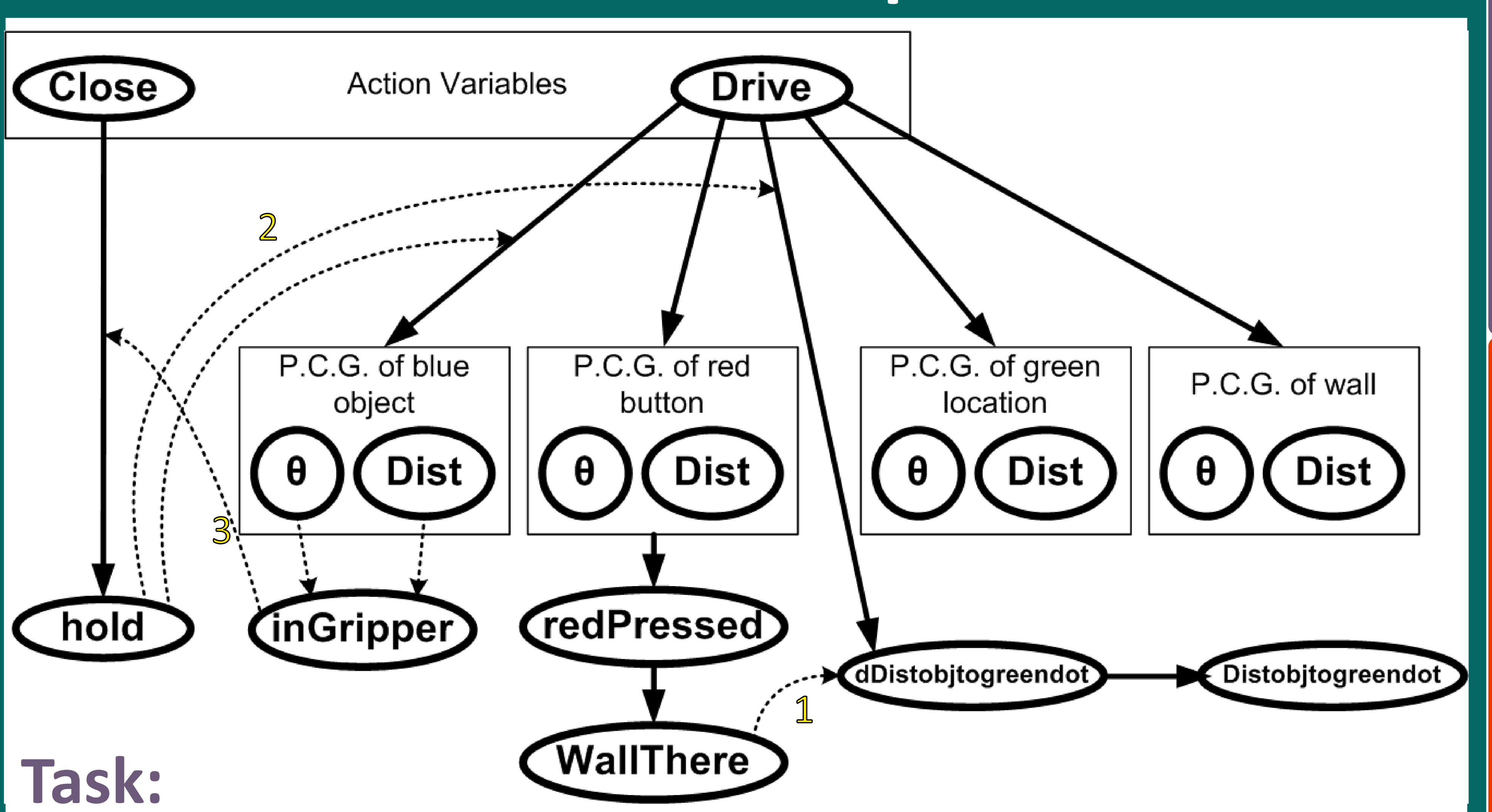
Items:

1. A robot with two wheels and a gripper.
2. A movable blue object
3. A green non-movable location
4. A red non-movable button
5. A wall around the green location

Constrains:

1. Wall prevents object from moving to green dot
2. Red button makes wall disappear.

Qualitative model of setup:



Task:

Distobjtogreendot -> 0 (move object to green dot)

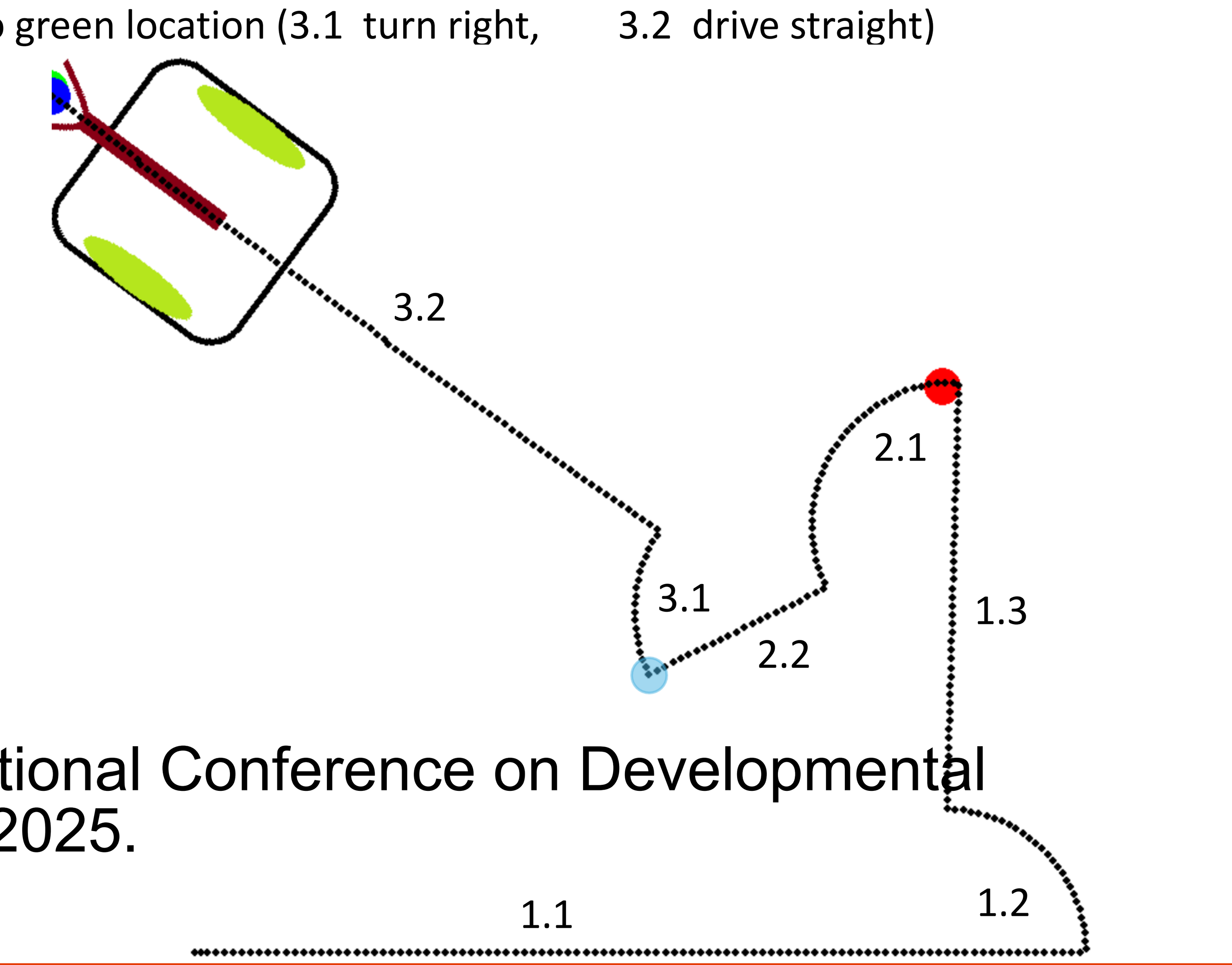
Relevant context variables when planning:

1. WallThere (to decrease Distobjtogreendot -> must remove wall by pressing red button)
2. Hold (to decrease Distobjtogreendot -> must hold object)
3. inGripper (to hold object -> must go to object and close gripper)

Result of experiment:

Generated action plan by planner:

1. Press red button (1.1 drive straight, 1.2 turn left, 1.3 drive straight)
2. Go to object (2.1 turn left, 2.2 drive straight)
3. Go to green location (3.1 turn right, 3.2 drive straight)



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