Hierarchical Learning for Human-Robot Collaboration

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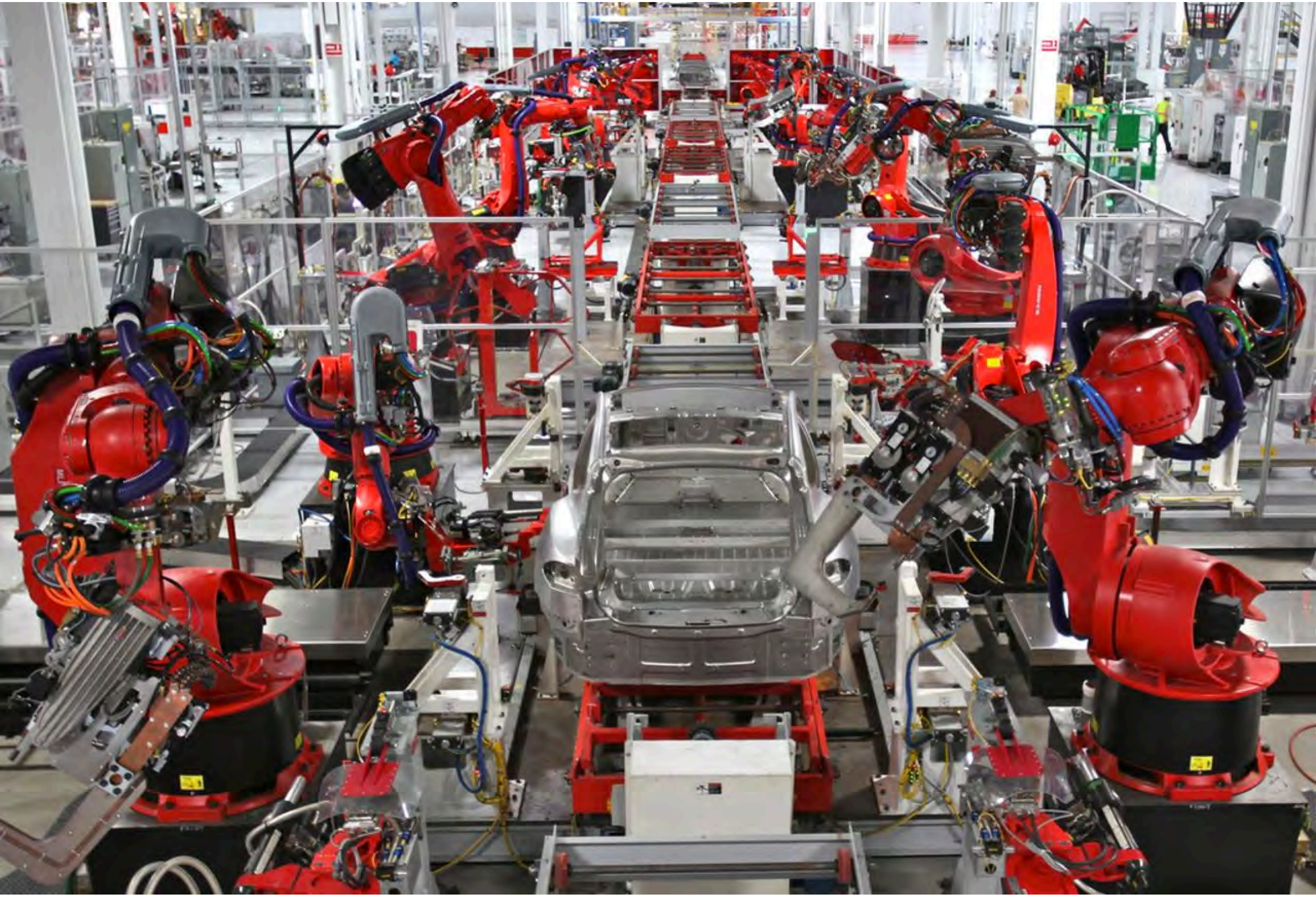
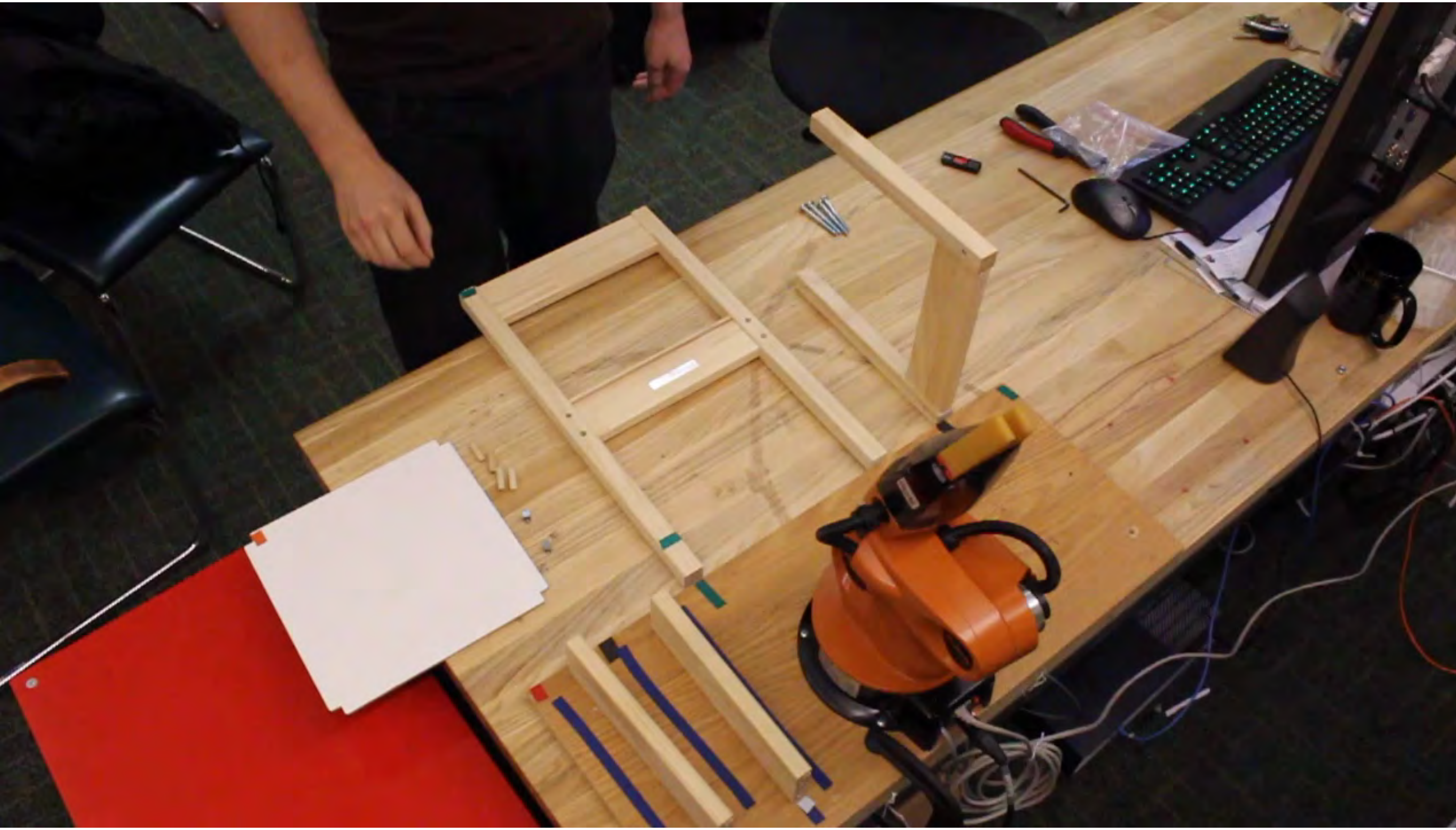
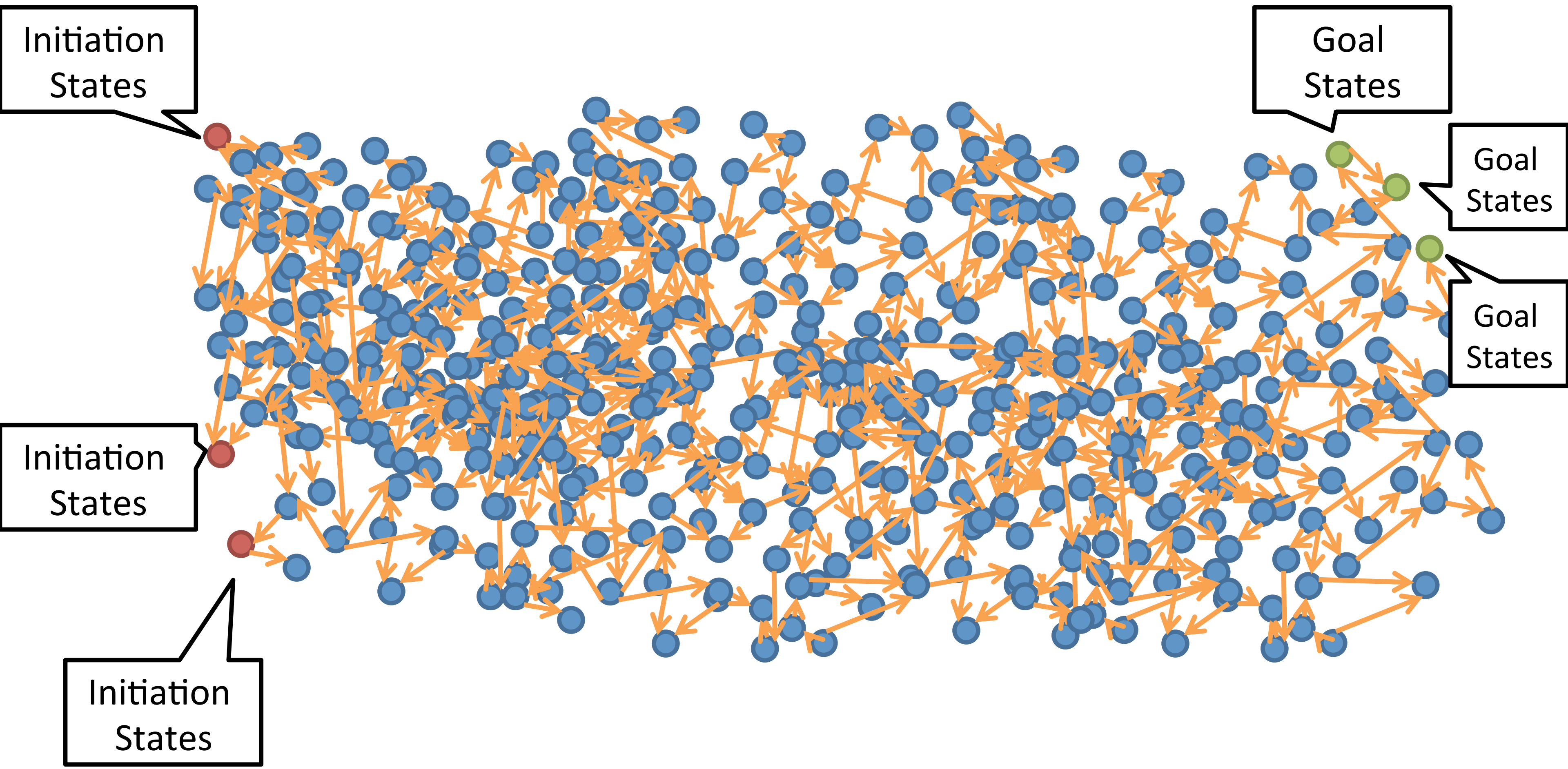


Sequential Manipulation Tasks



SMDPs Modeling Tasks Are Complex



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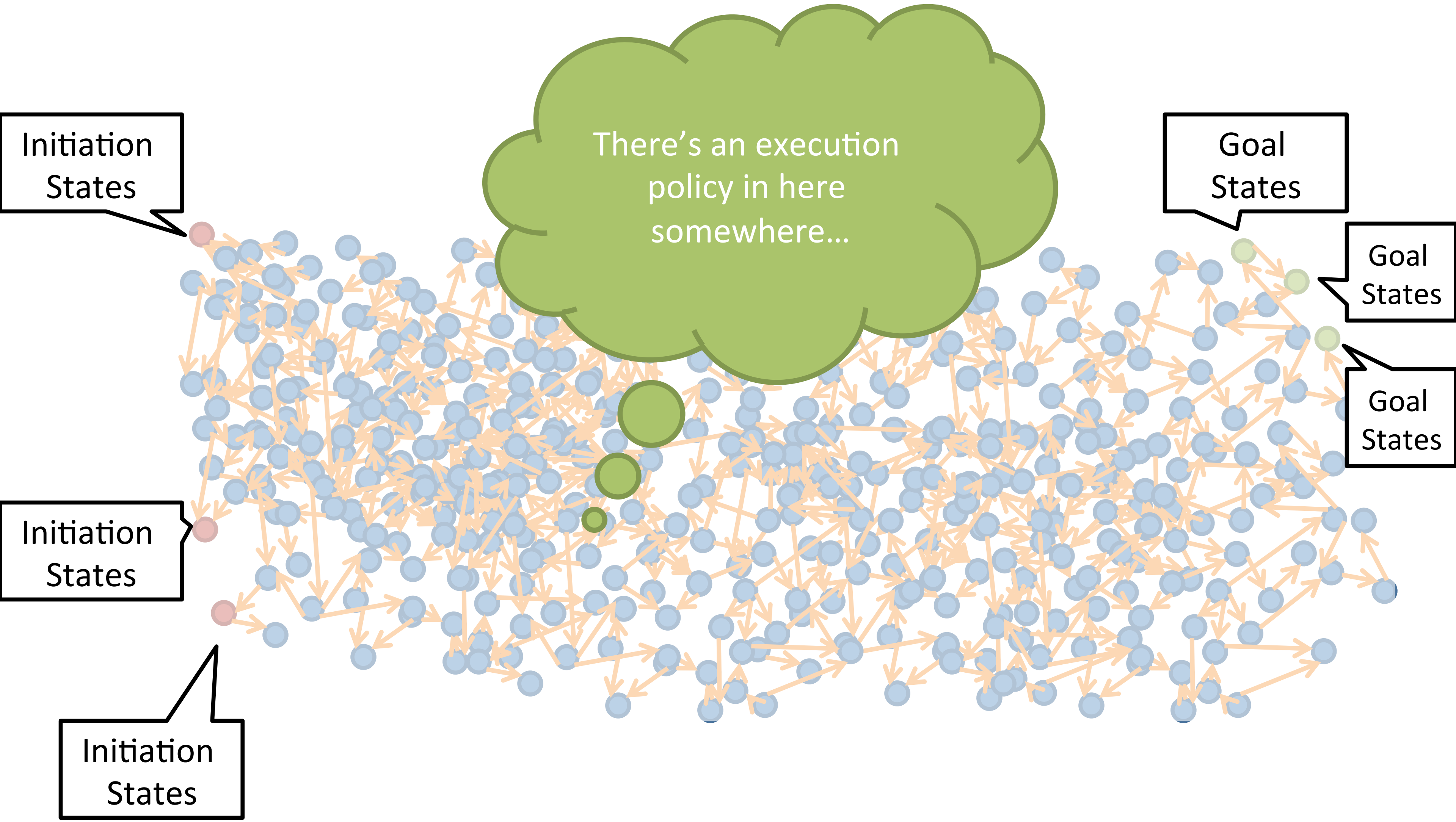

Near-Term Assistive Scenarios

Changes as we consider Collaborative Manufacturing

- Keep many of our pillars
  - Observations of sequential manipulation tasks
  - Existing methods for learning from demonstration
  - Focus on execution policies
- Adapt to collaborative setting
  - Move away from flat representations
  - Move away from divide-and-conquer planning mechanisms
  - Consider collaboration in a broad sense

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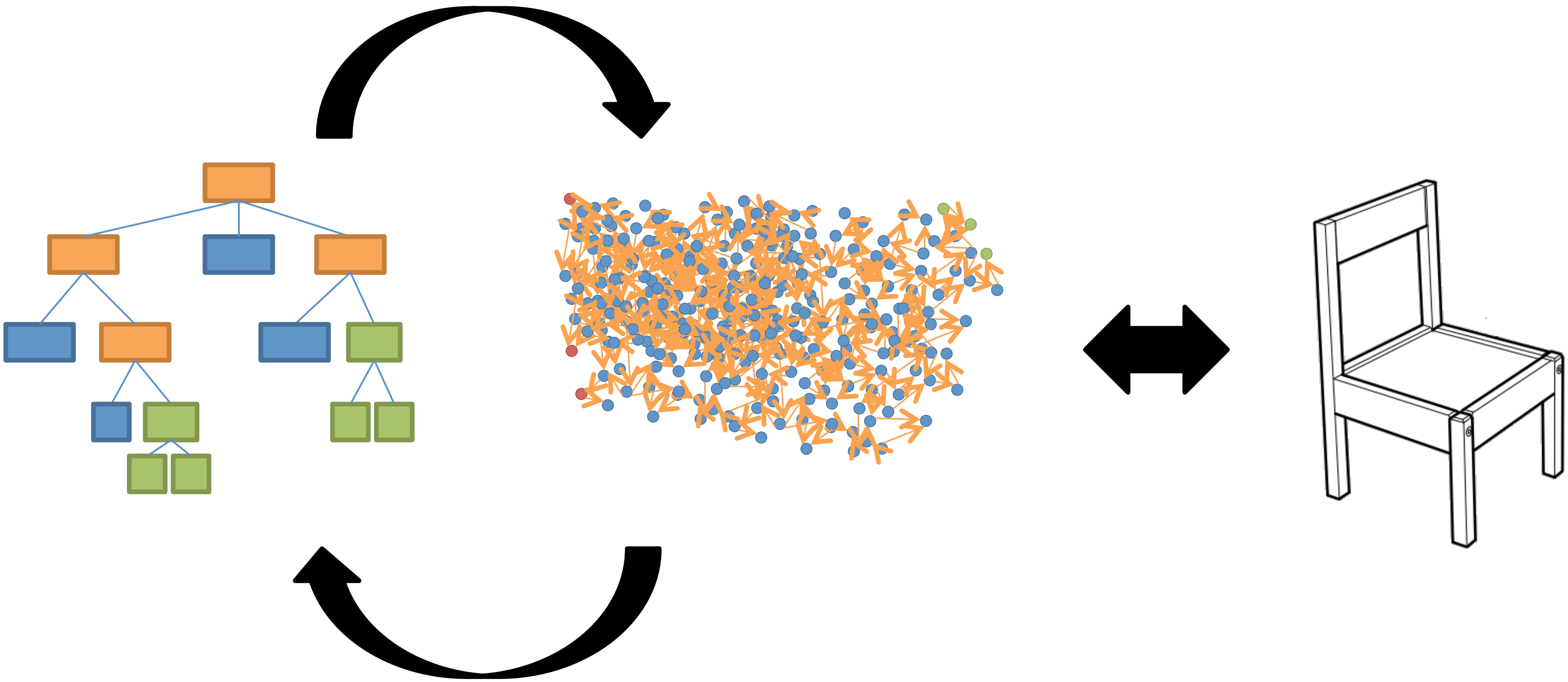
Benefits of Hierarchical Structure

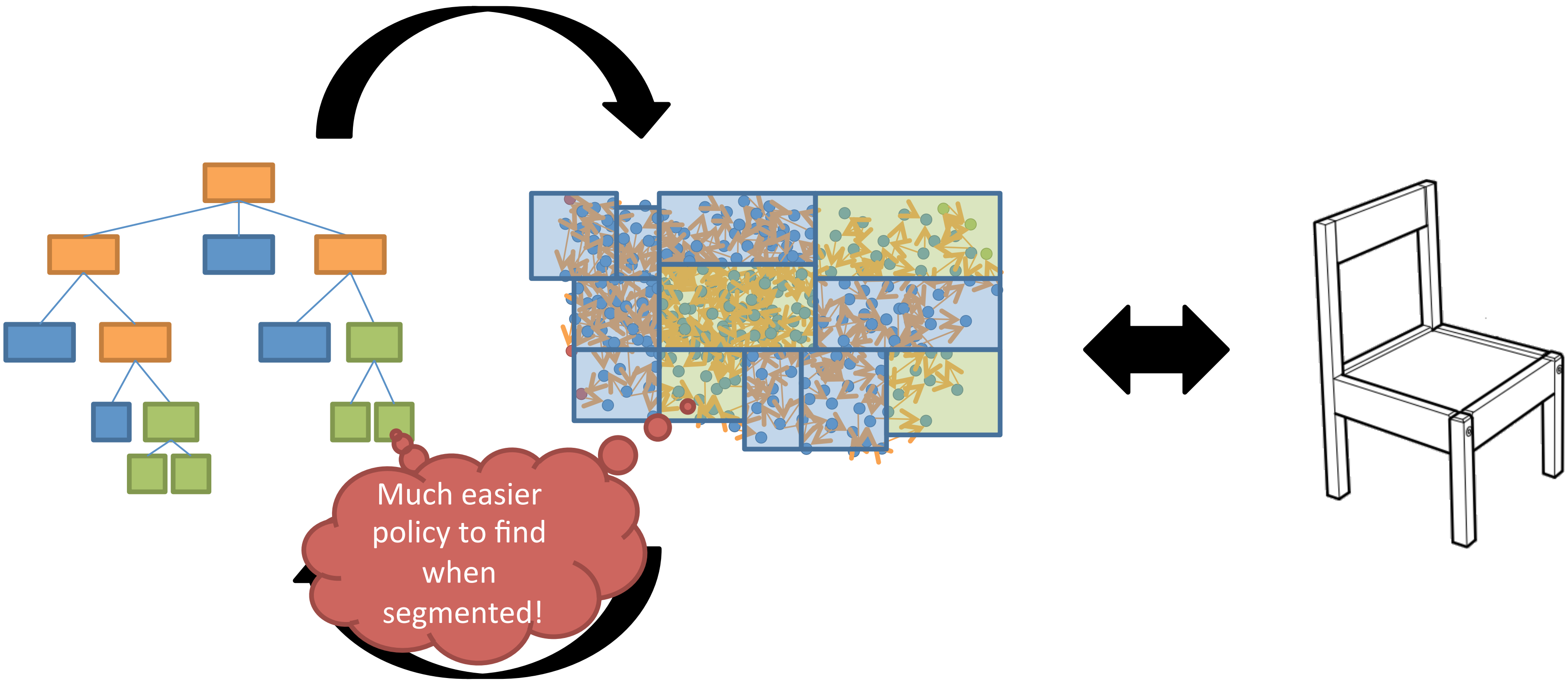
- Benefits of hierarchical structure:
  - Reduce dimensionality of policy search space

Leverage Hierarchical Structure



Hierarchical structure within the SMDP can be used to make the policy search more tractable

Leverage Hierarchical Structure



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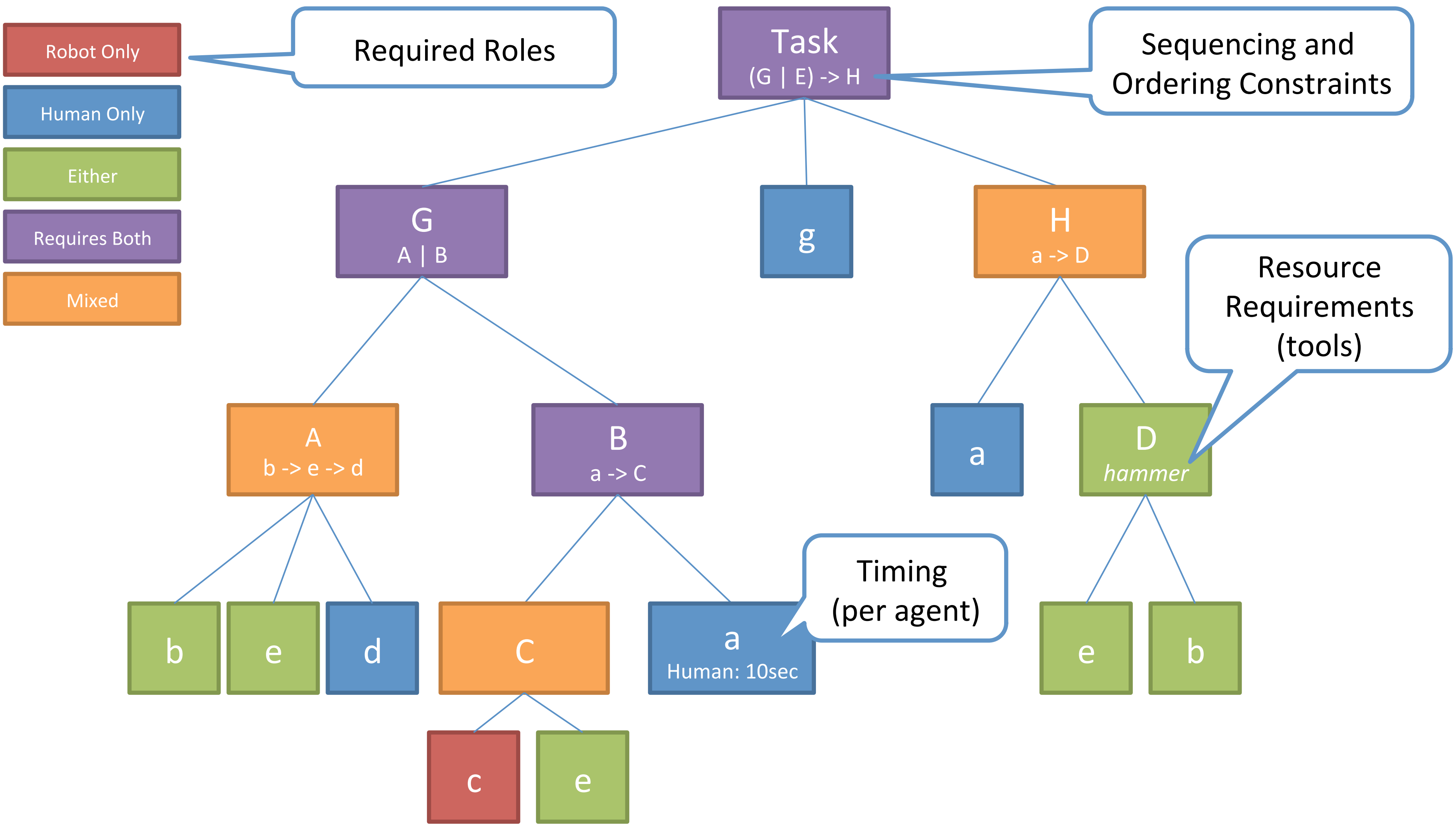
  - Multi-agent task allocation
    - Parallel execution
    - Preferential allocation

Augmenting Hierarchical Plans with Social Metadata



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    - Parallel execution
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  - Transparency
    - Similarity of cognitive models
    - Ability to leverage communication

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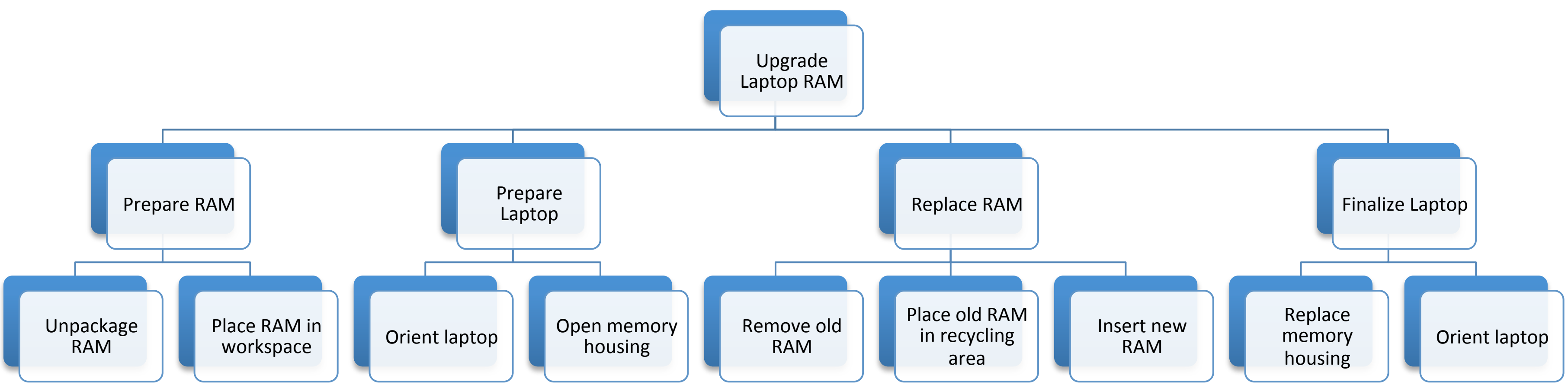
  - Transparency
    - Similarity of cognitive models
    - Ability to leverage communication
- Disadvantages:
  - How do we build the hierarchy from observation?

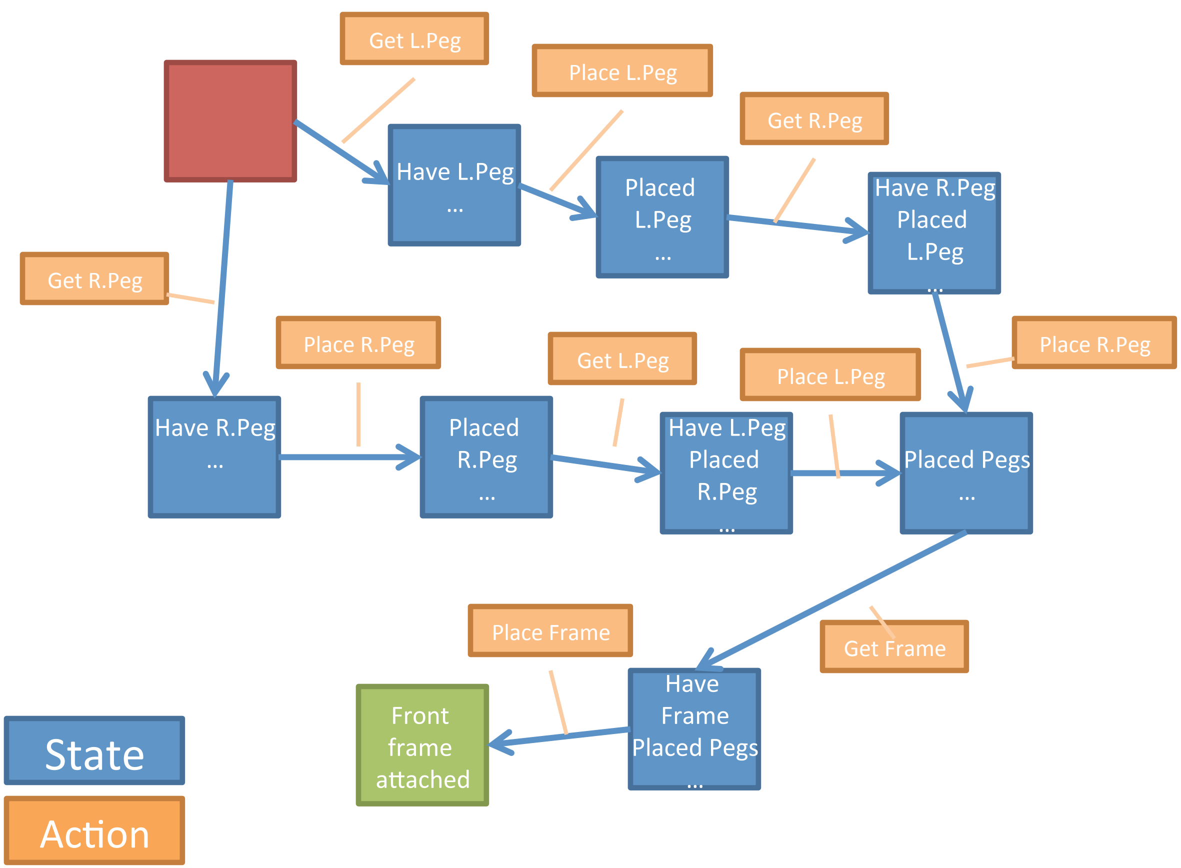
Building Hierarchical Structure from Sequential Observations

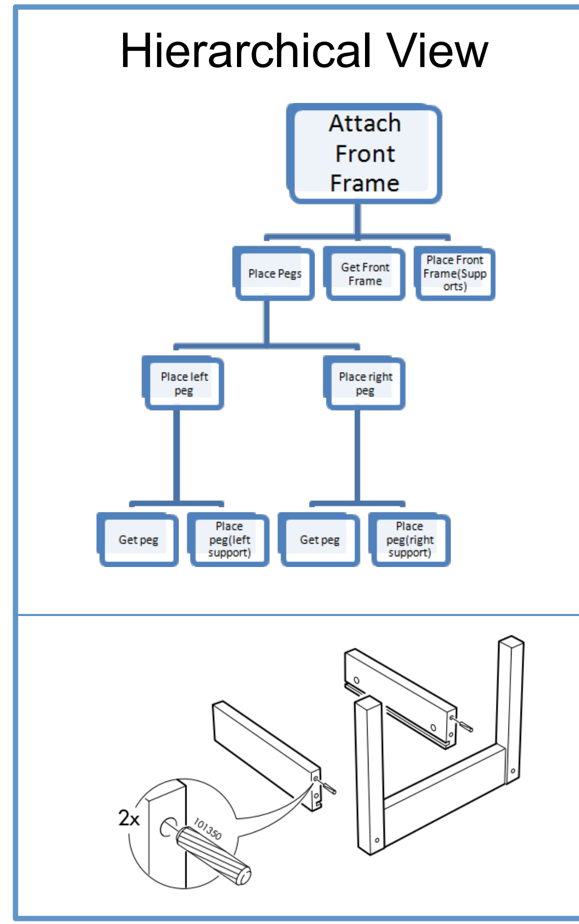
Performance by worker "A"

Performance by worker "B"



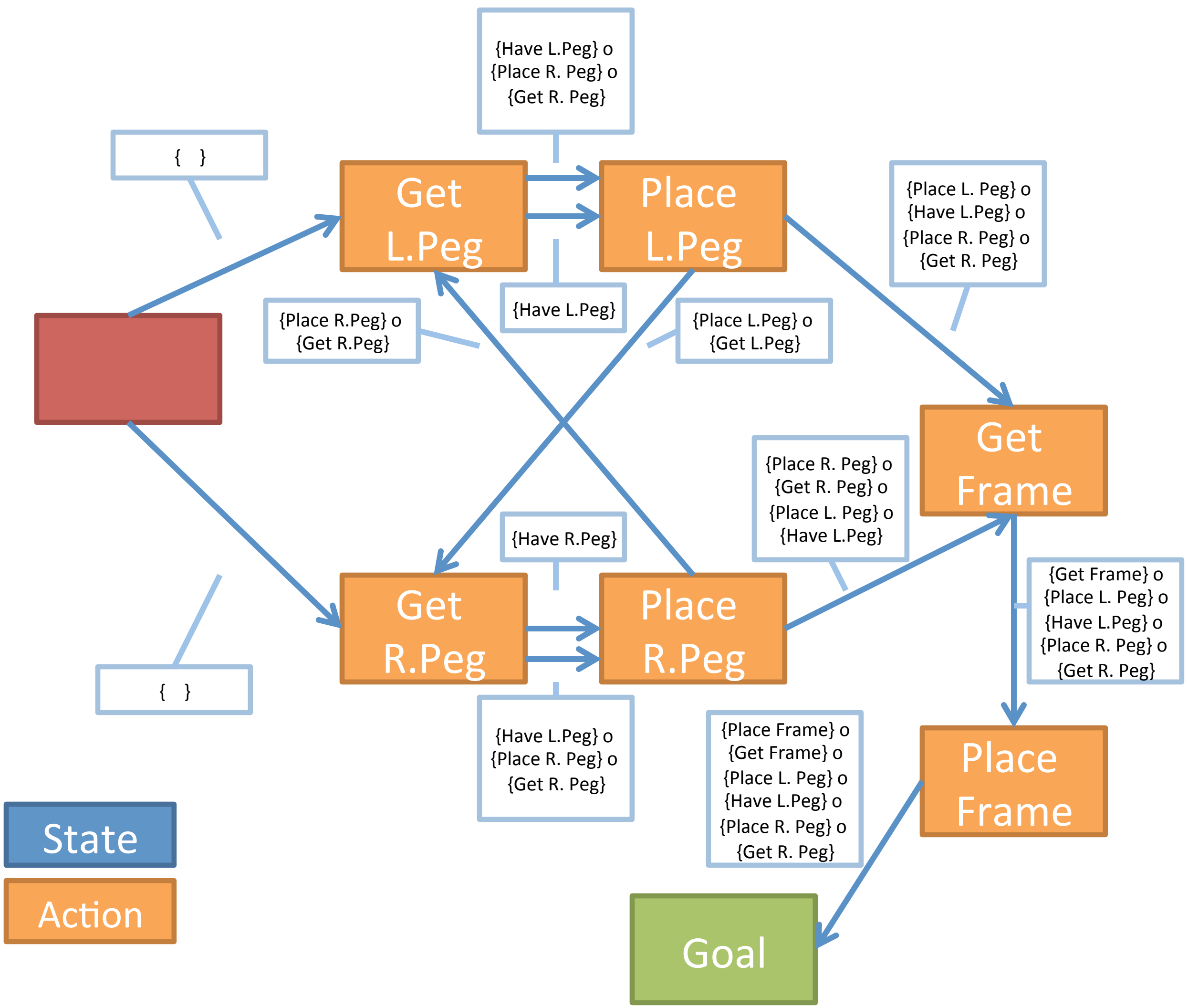
SMDP of “Attach Front Frame” Subtask





(Hayes & Scassellati, IROS 2014)

SMDP-Conjugate of “Attach Front Frame” Subtask

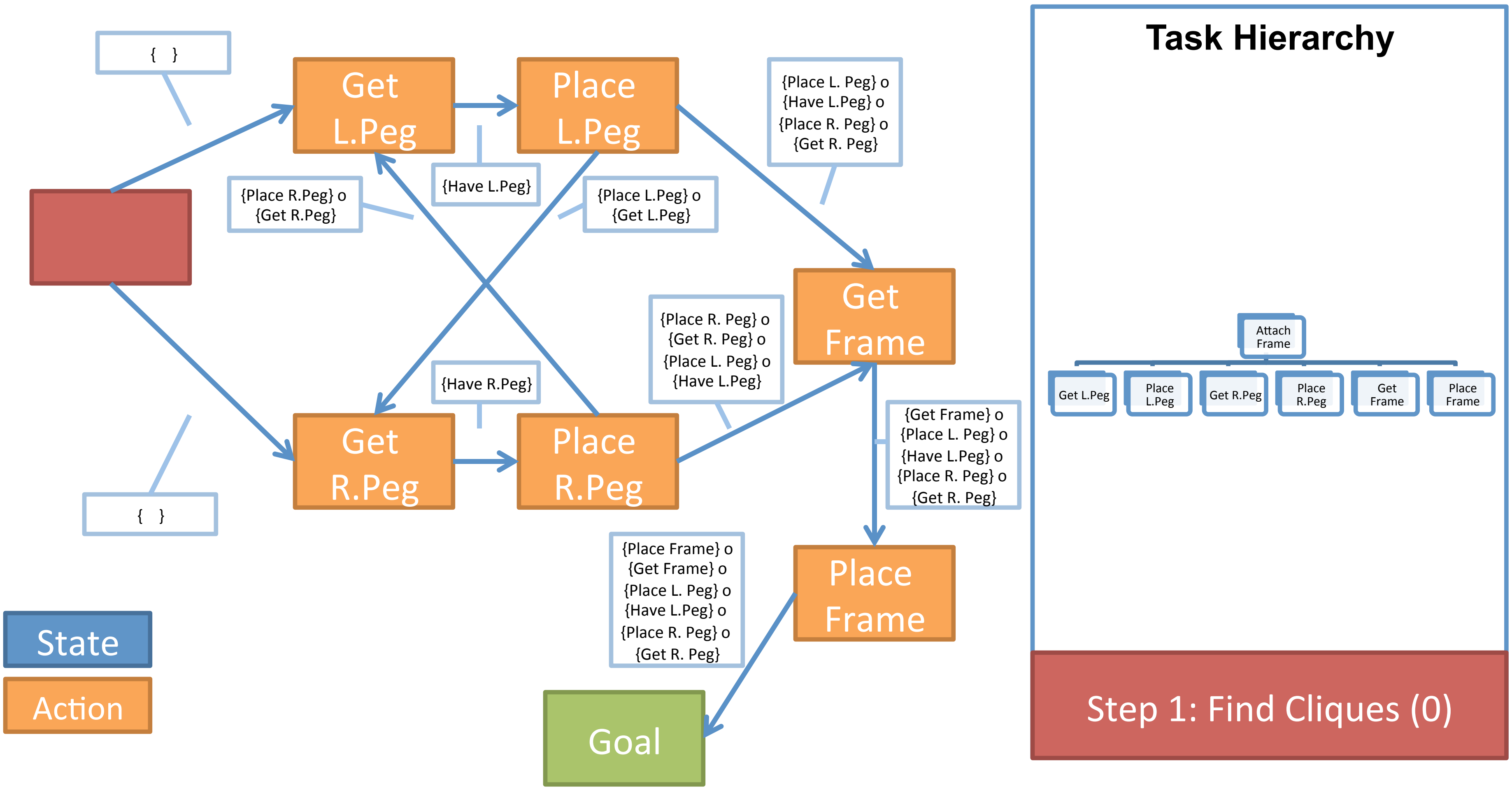


SMDP Conjugate: Actions become vertices and required state is described on edges as a composition of motor primitives.

Edges are labeled with transition **requirements** – A composition of motor primitives describing the world state required to use that edge.

Vertices contain motor primitives that can be executed only upon **arriving** in the node.

Building Hierarchical Structure



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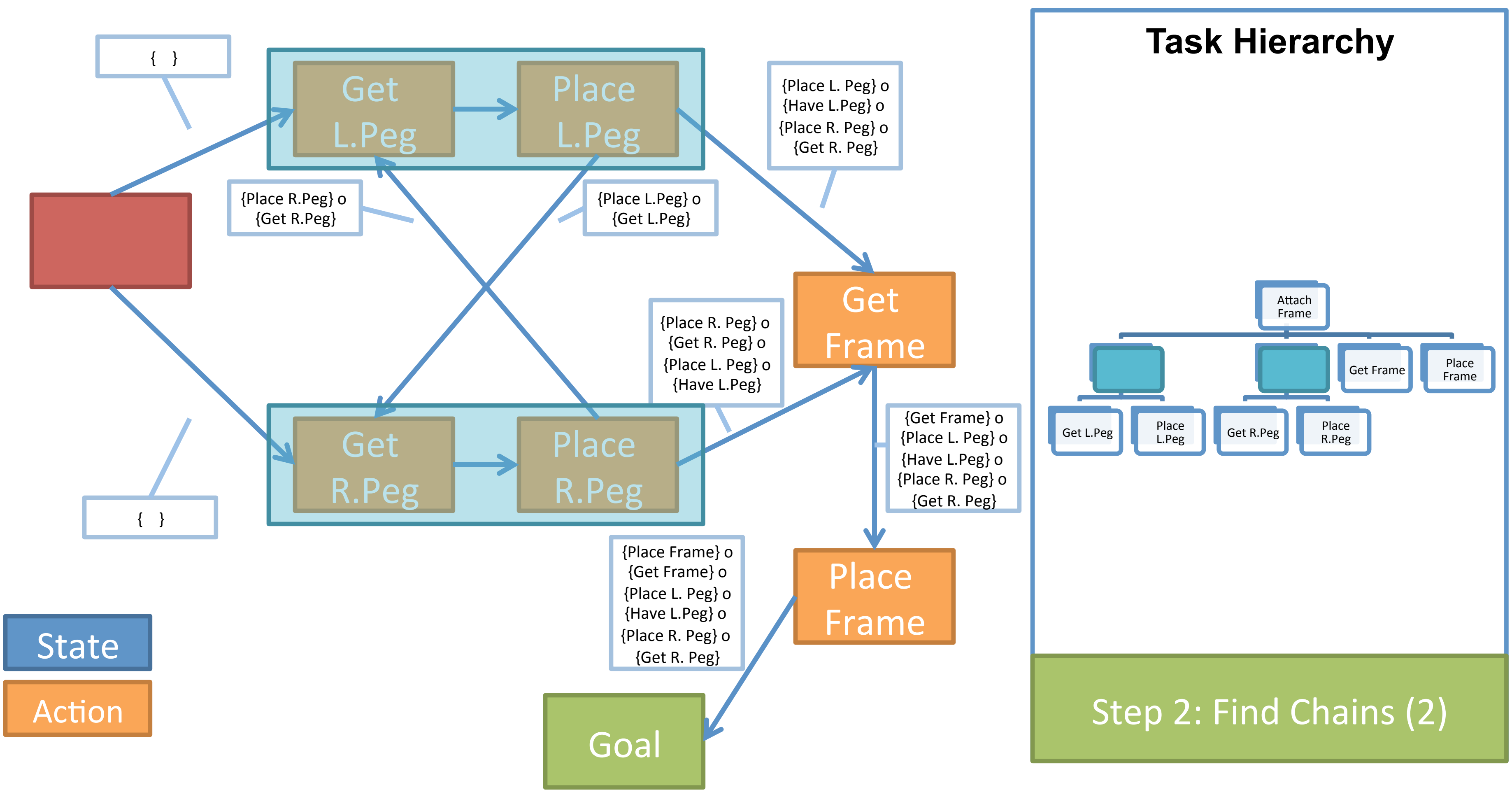

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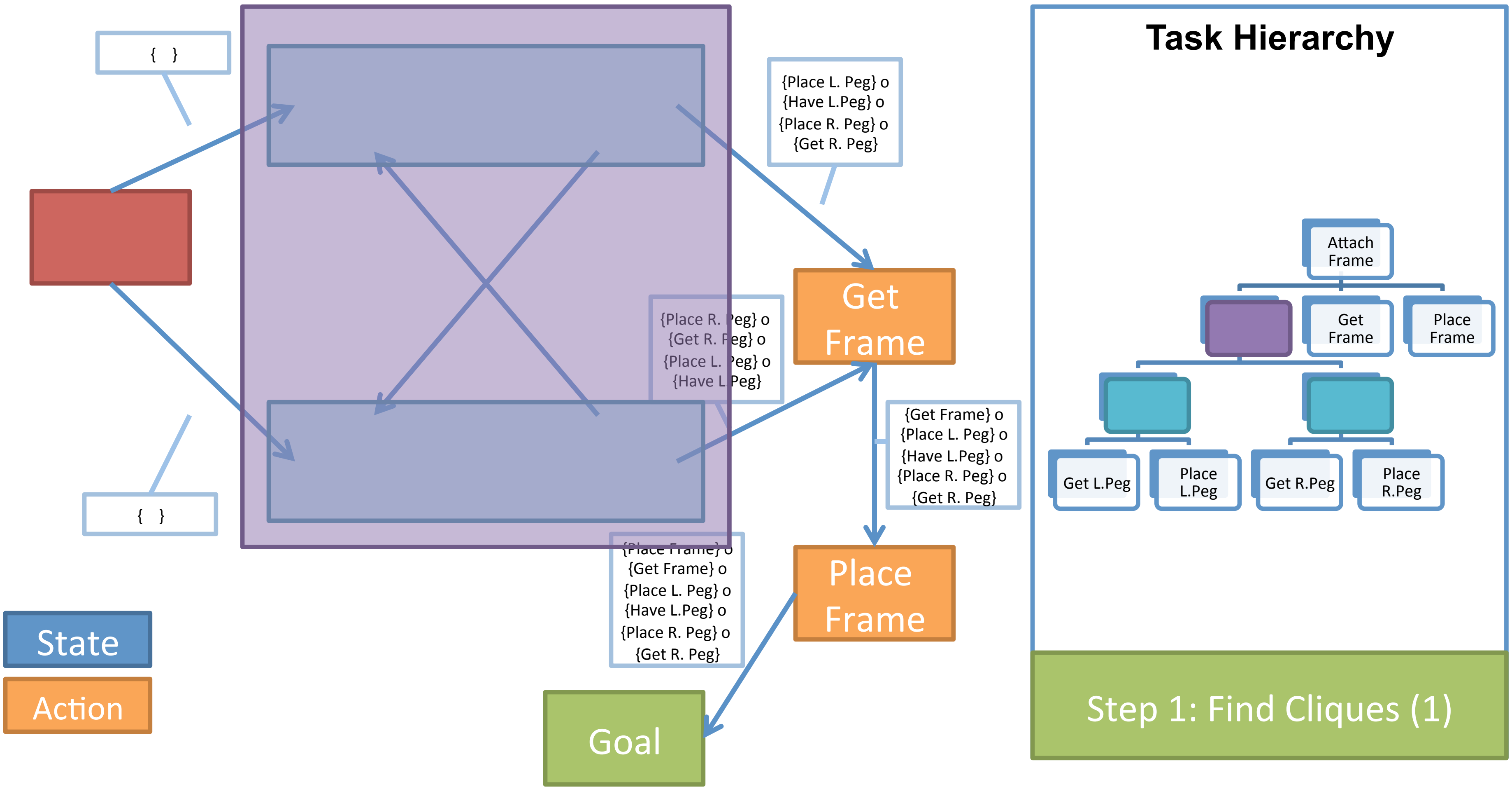
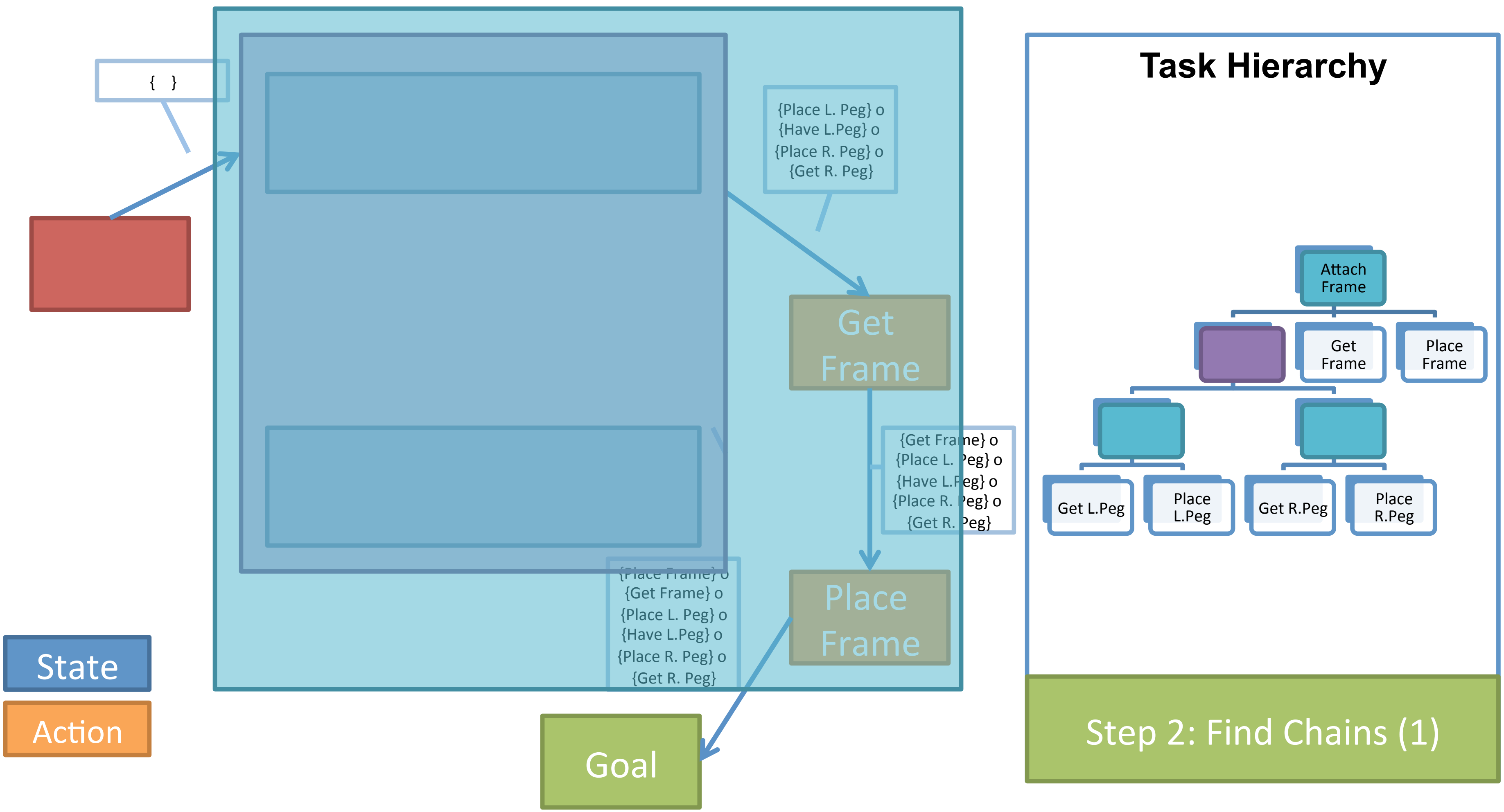


Building Hierarchical Structure



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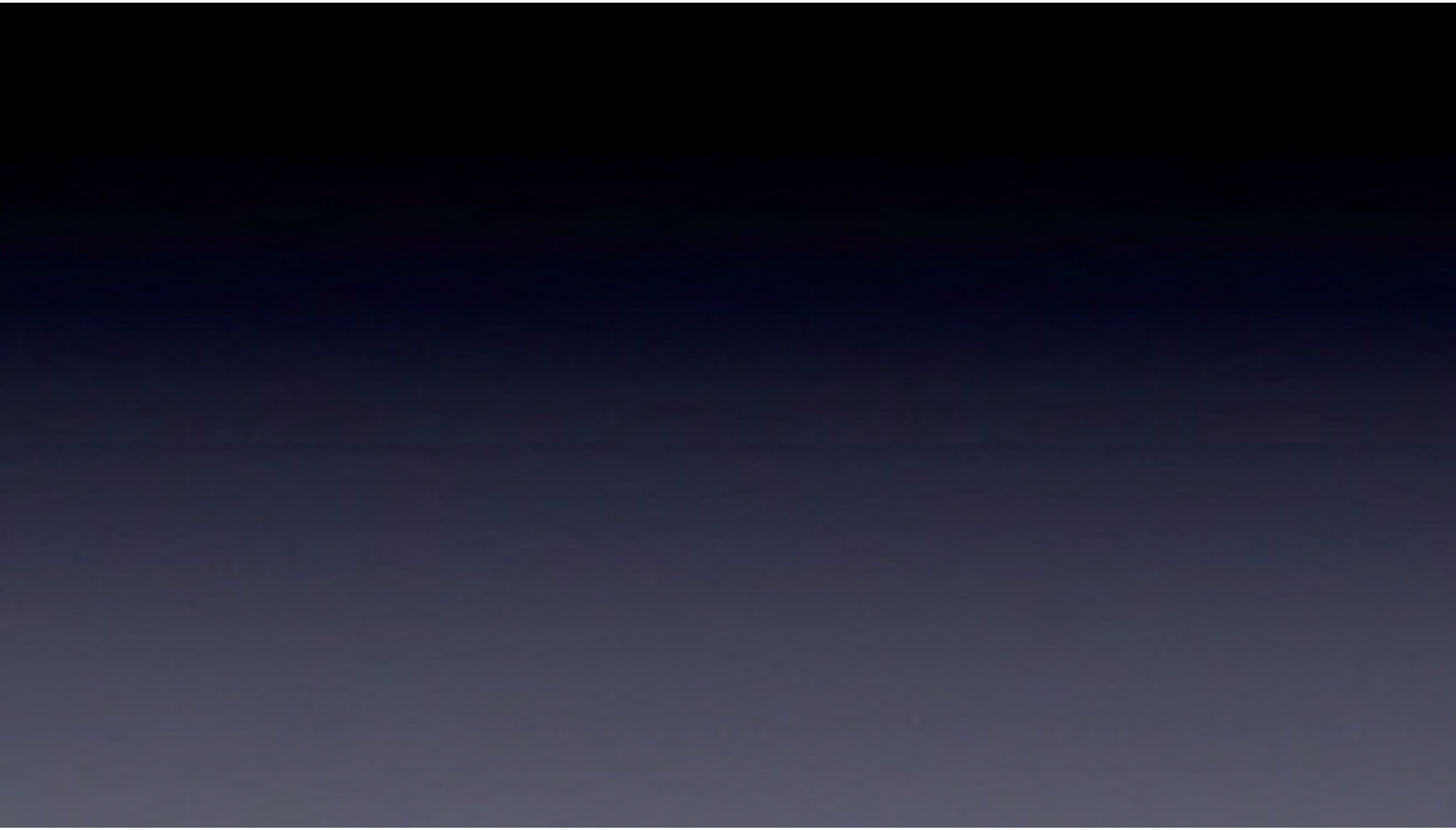
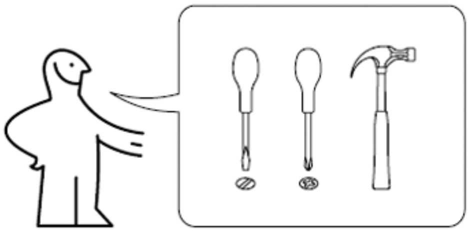
Supportive Behaviors



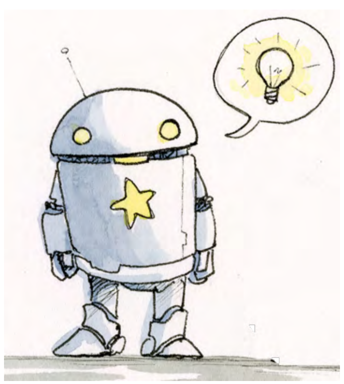
Can we do better than LfD-based Methods?



Demonstration-based Methods

Human figures out ***how*** and ***when*** the robot can be helpful

- \+ Quickly enables useful, helpful actions.
- − Does not scale with task count!
- − Requires human expert



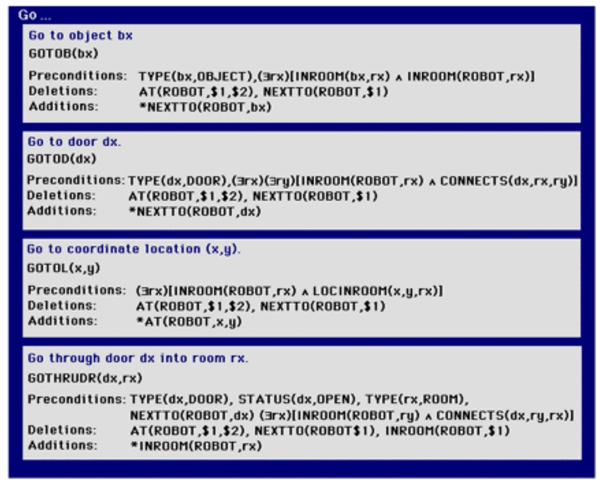
Planner-based Methods

Robot figures out ***how*** and ***when*** it can be helpful

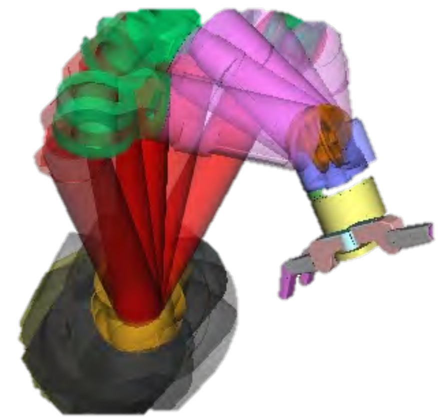
- Allows for novel behaviors to be discovered
- Enables deeper task comprehension and action understanding

Generating Supportive Behaviors

Perspective Taking



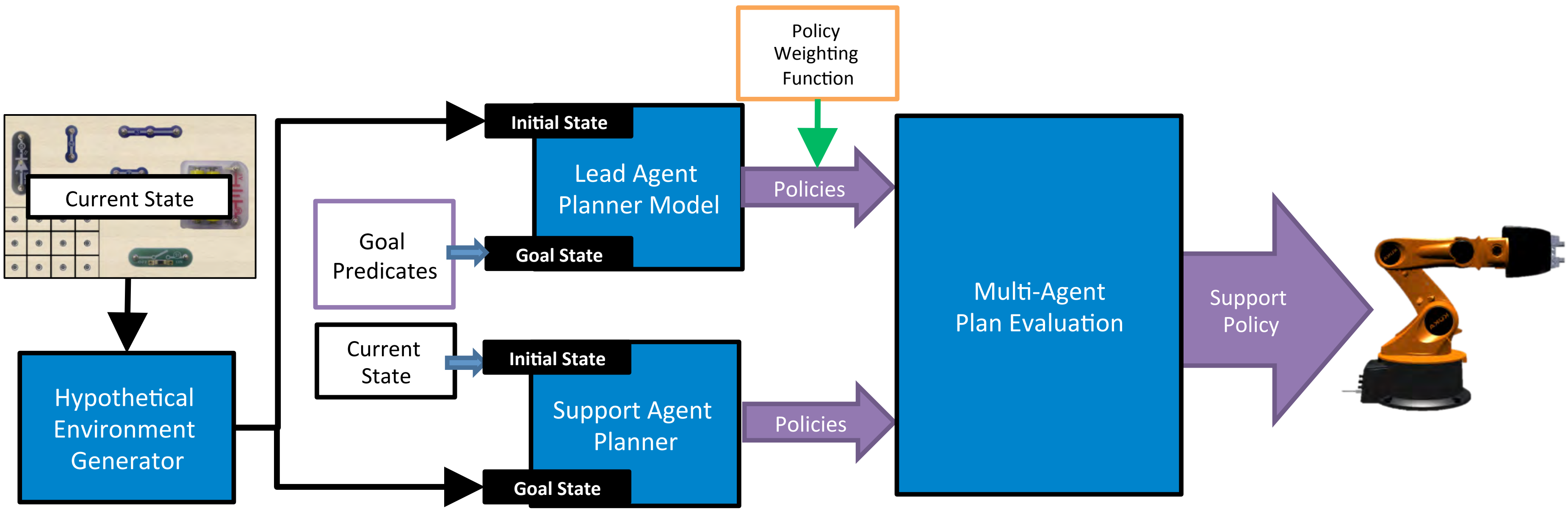
Symbolic planning



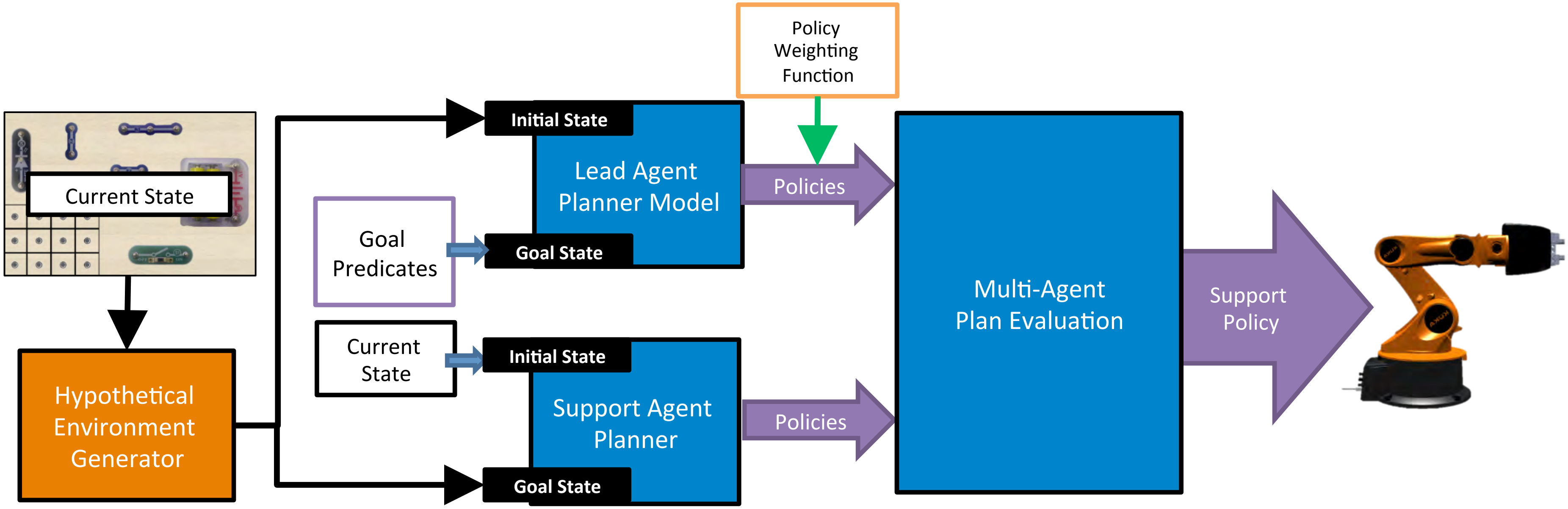
Motion planning

Autonomously Generated Supportive Behaviors

Supportive Behavior Planning

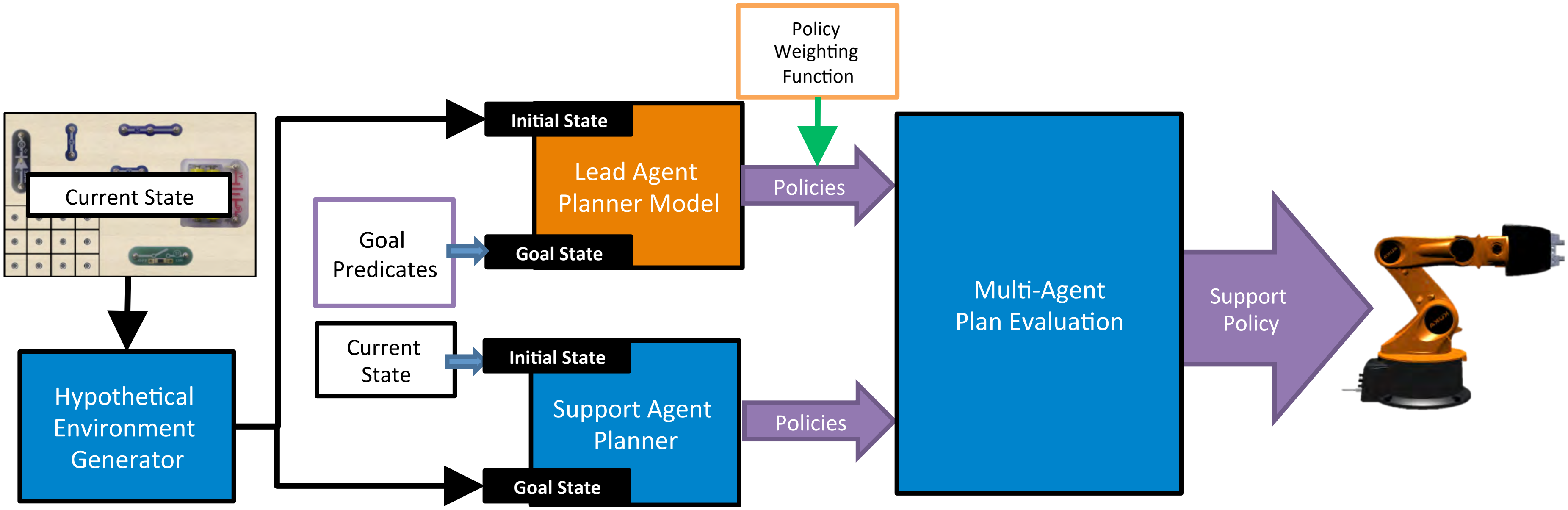


Supportive Behavior Planning



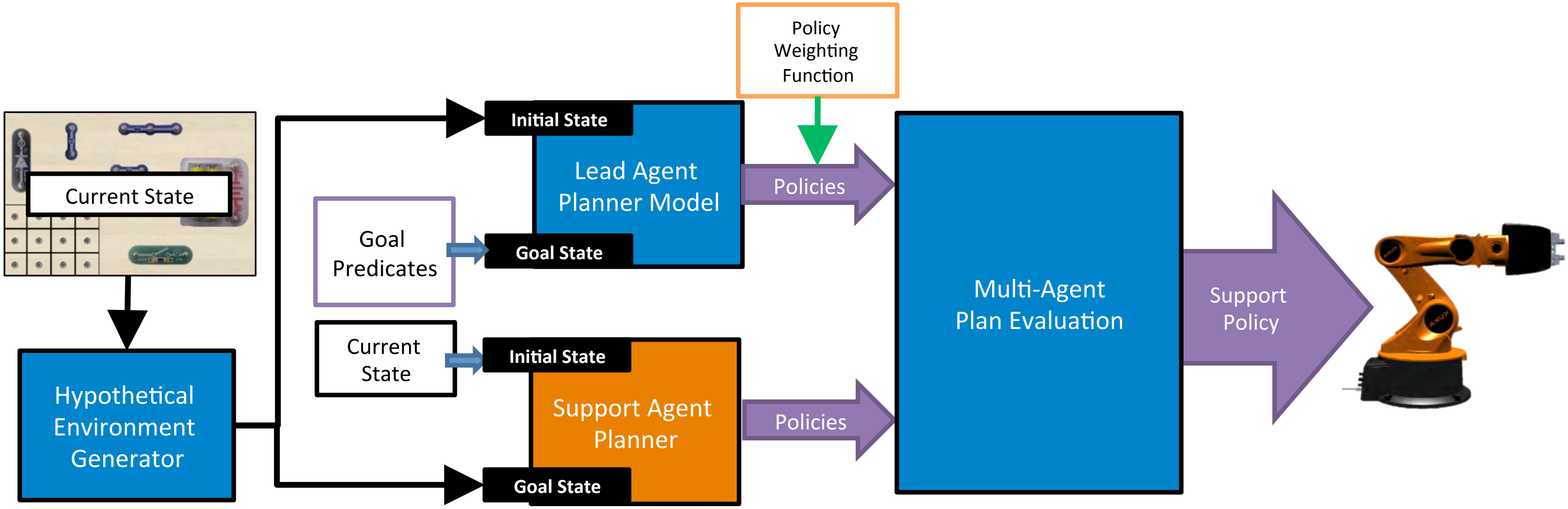
- Hypothesize future world states based on their plans

Supportive Behavior Planning



- Hypothesize future world states based on their plans
- Predict lead agent behavior using a user model

Supportive Behavior Planning



- Hypothesize future world states based on their plans
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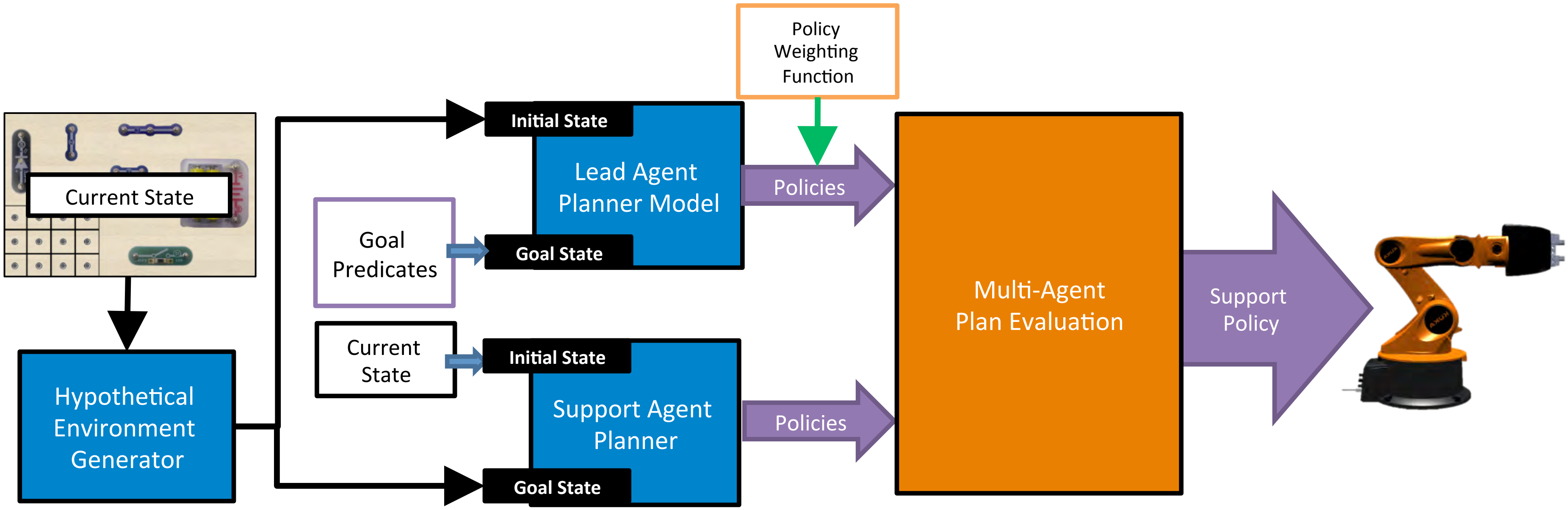
- Plan supportive actions that would simplify achieving this world state (or prevent sub-optimal plans)

Supportive Behavior Planning



- Hypothesize future world states based on their plans
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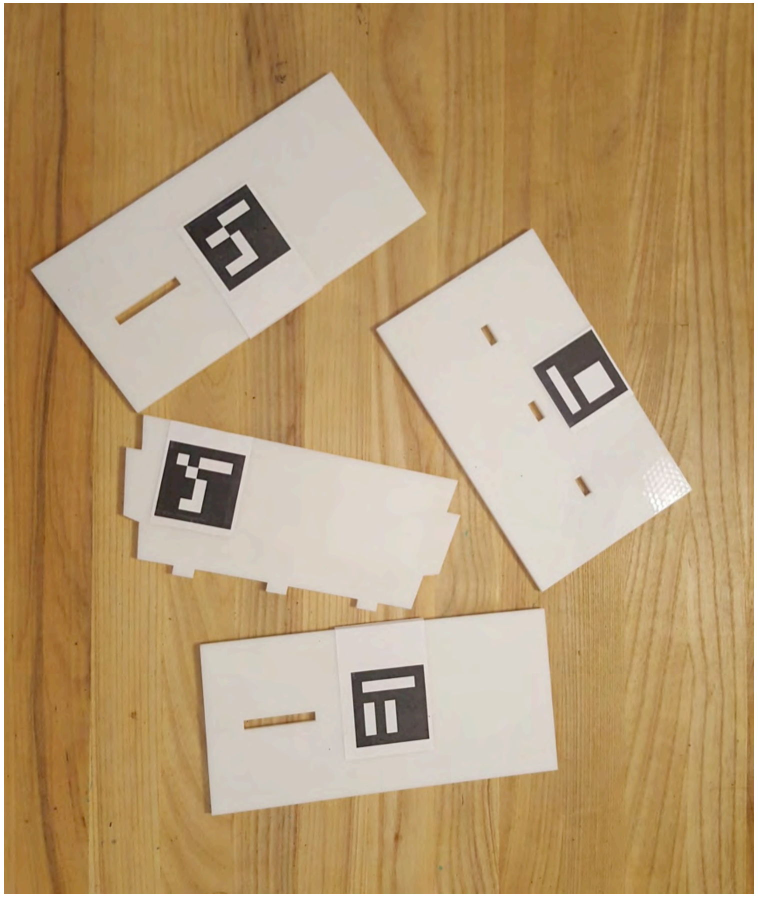
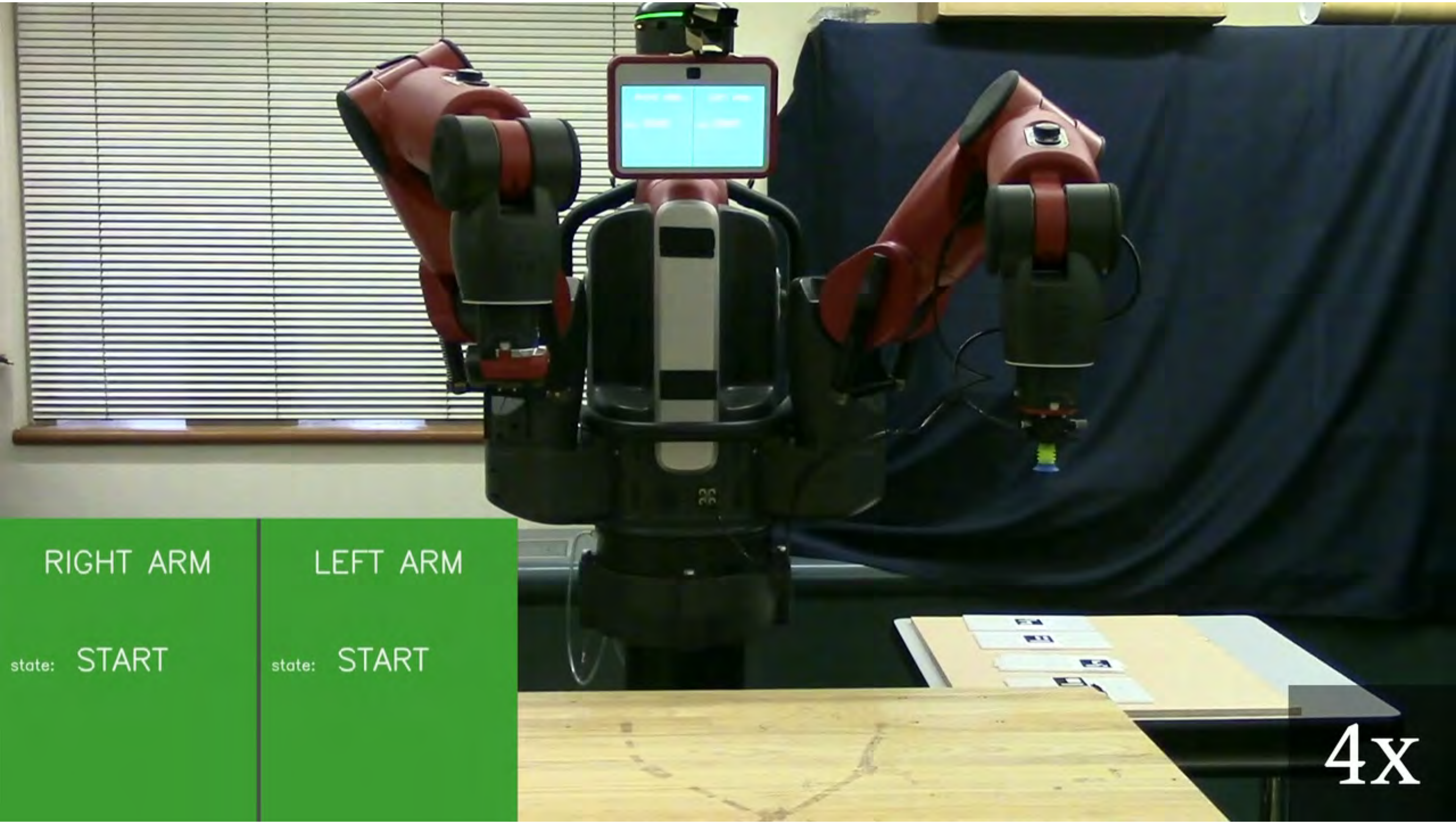
- Evaluate multi-agent plan

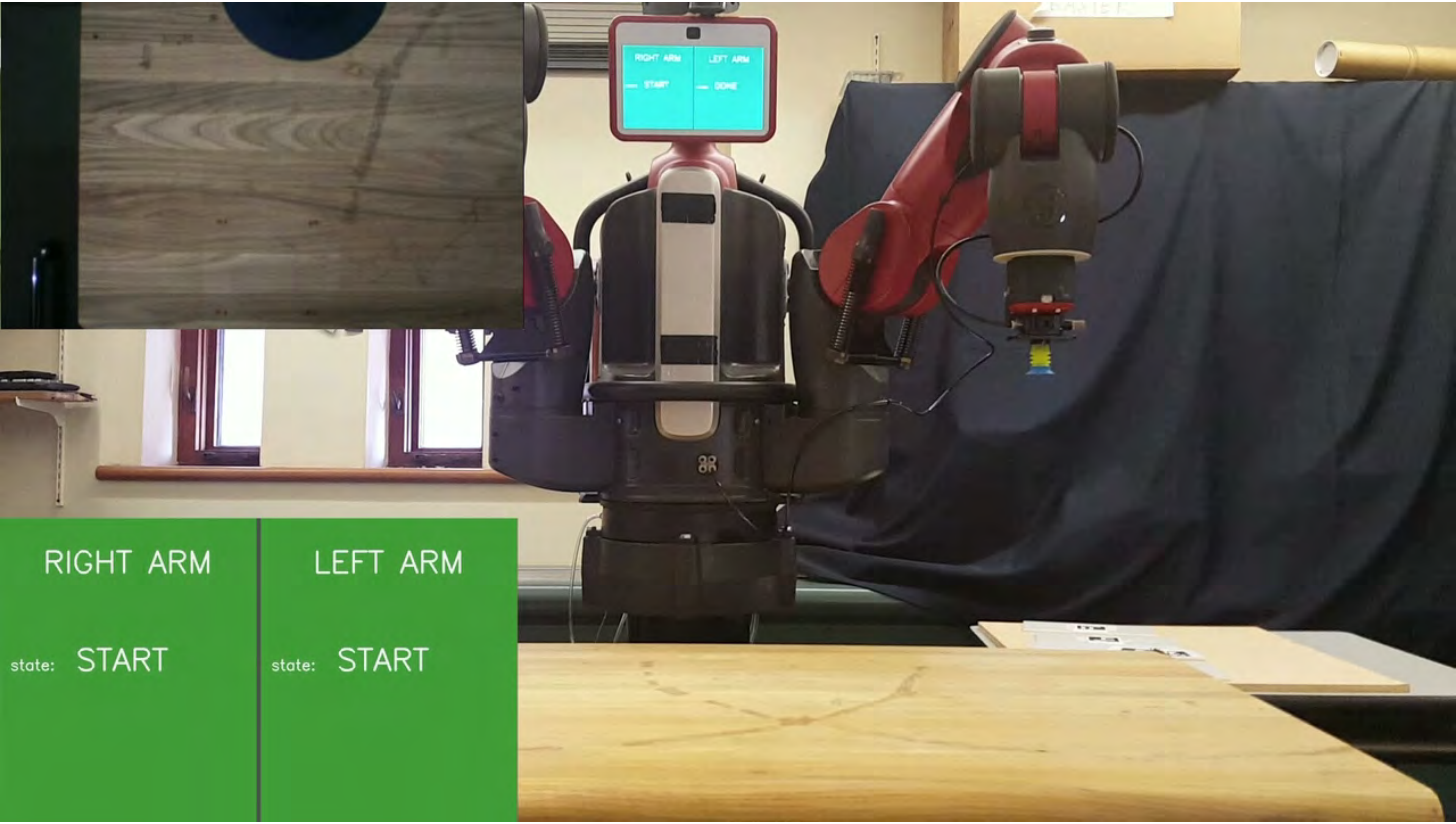
Simplified manipulation task



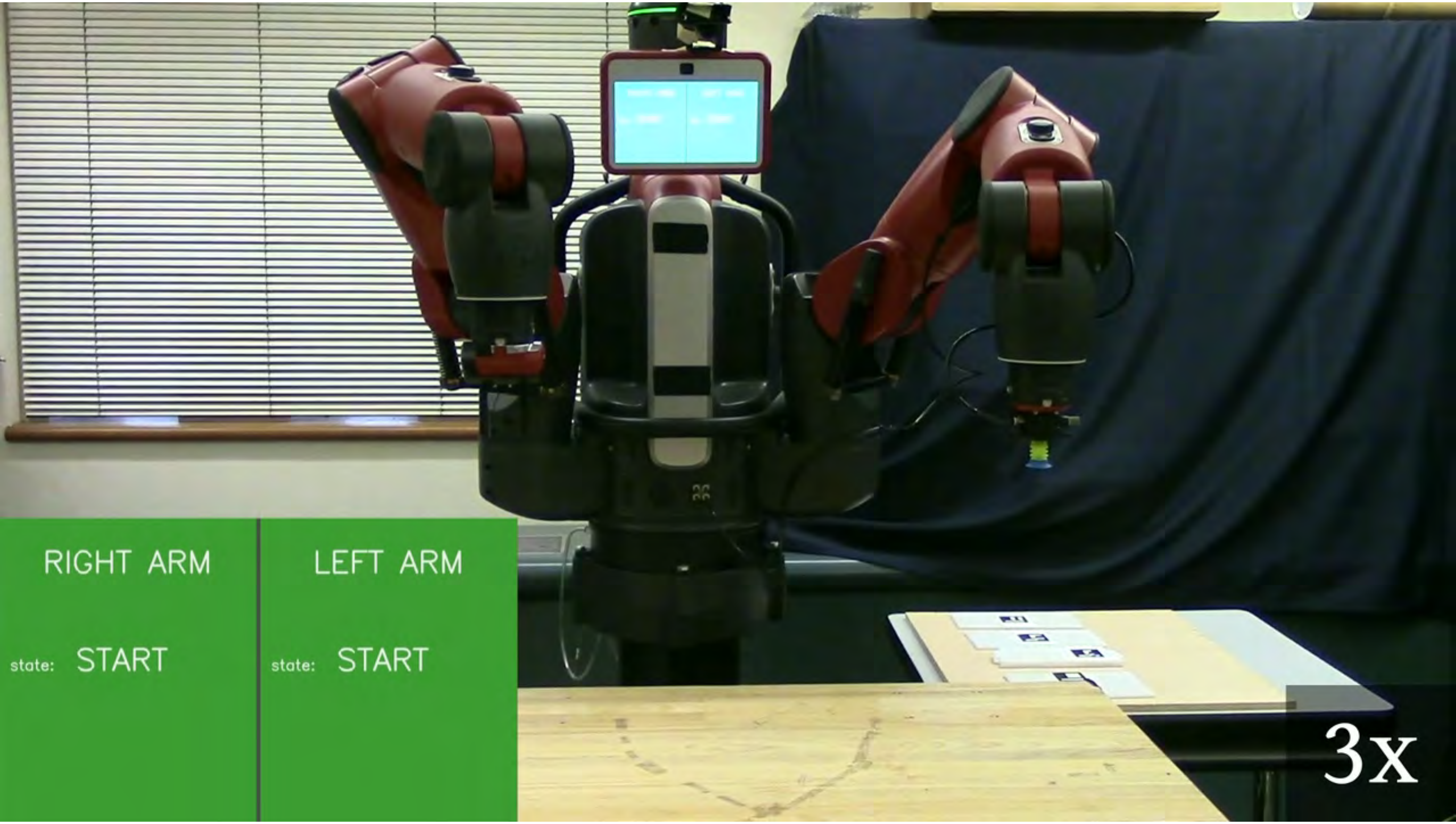
Supportive Action for Bench Assembly



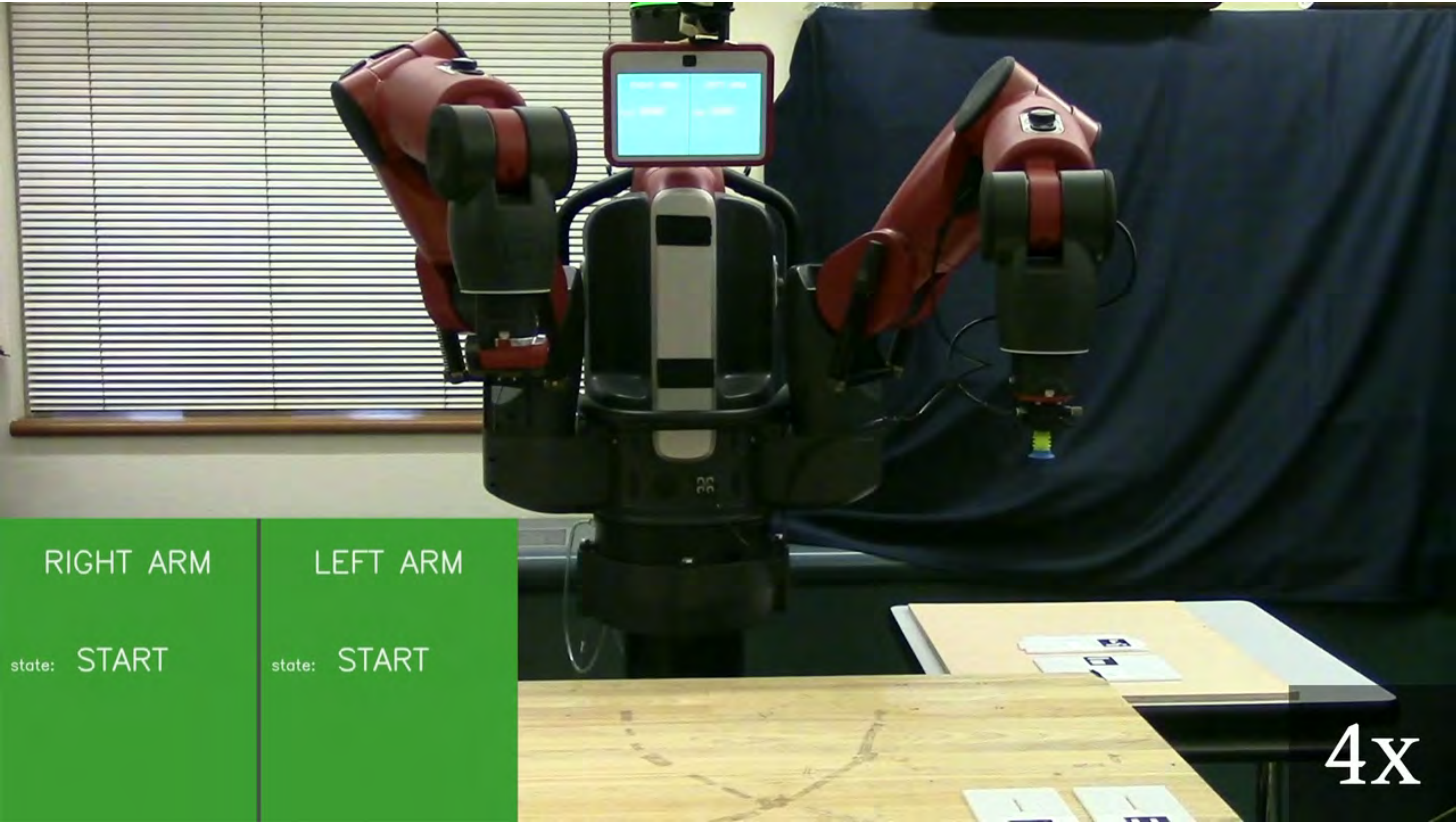
Simplified Vision, Control



Failure Recovery



Preferences in Task Assignment



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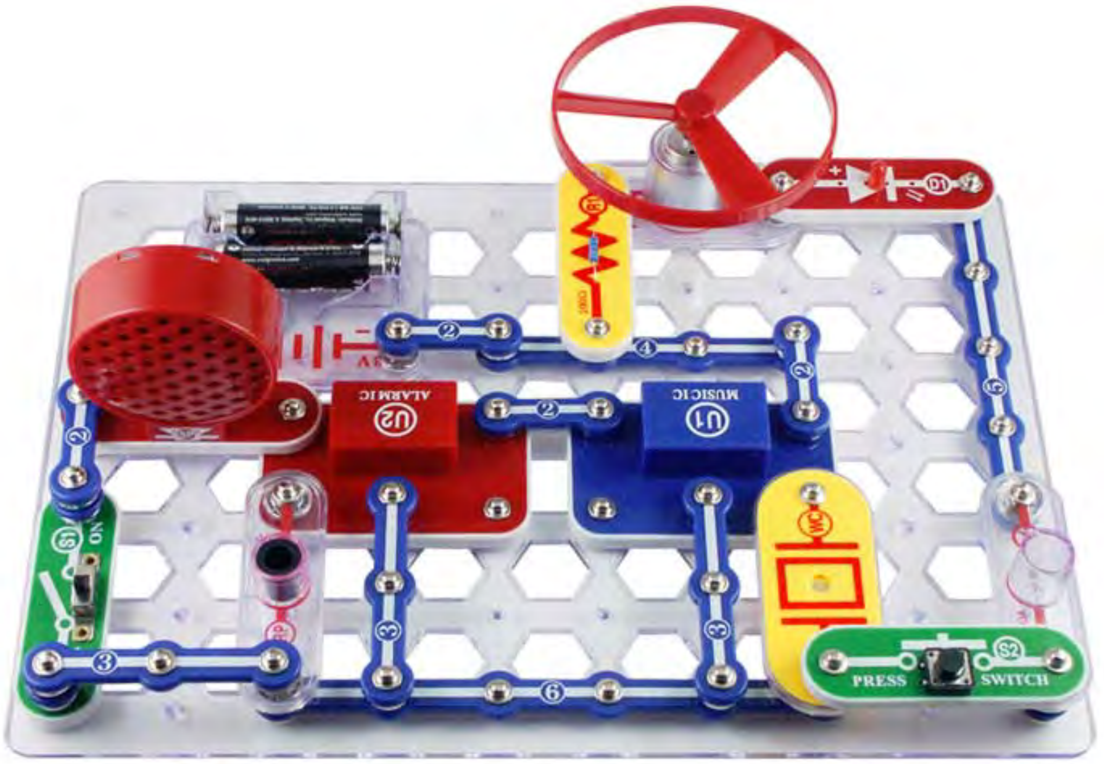
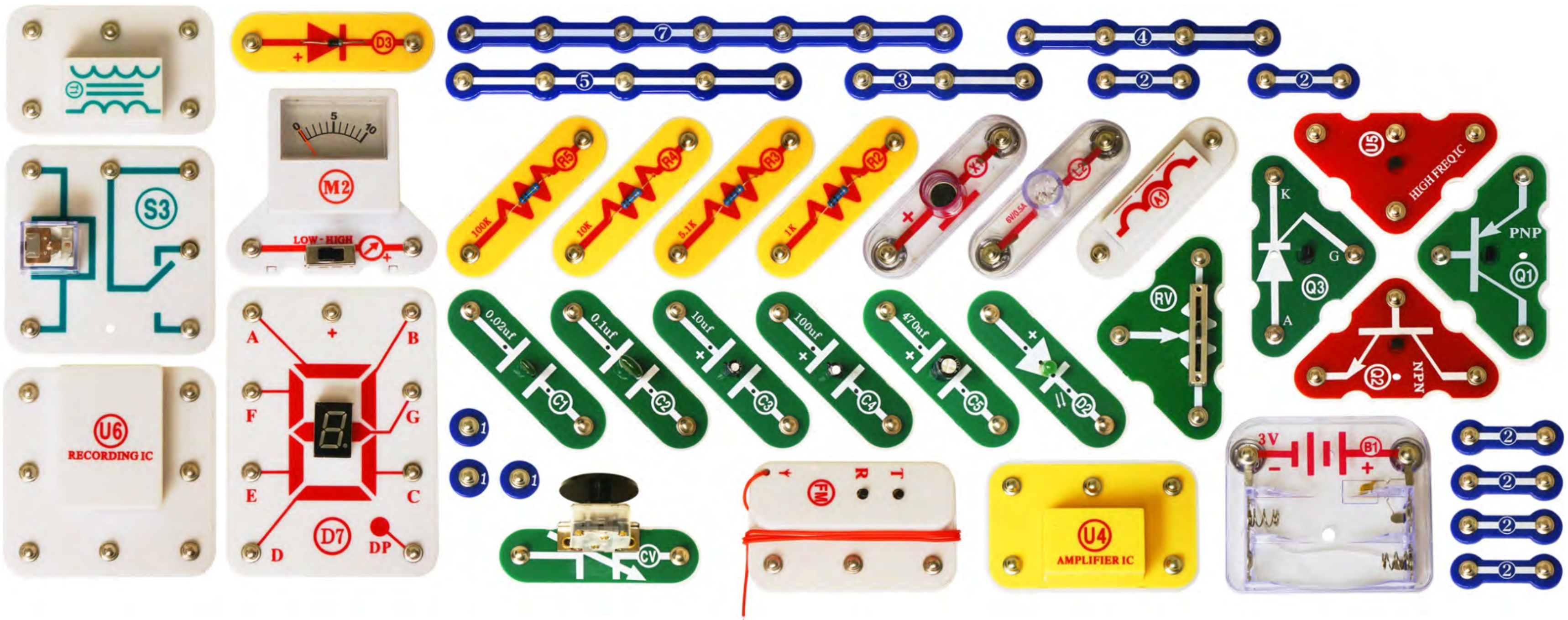
Application Domain: SnapCircuits



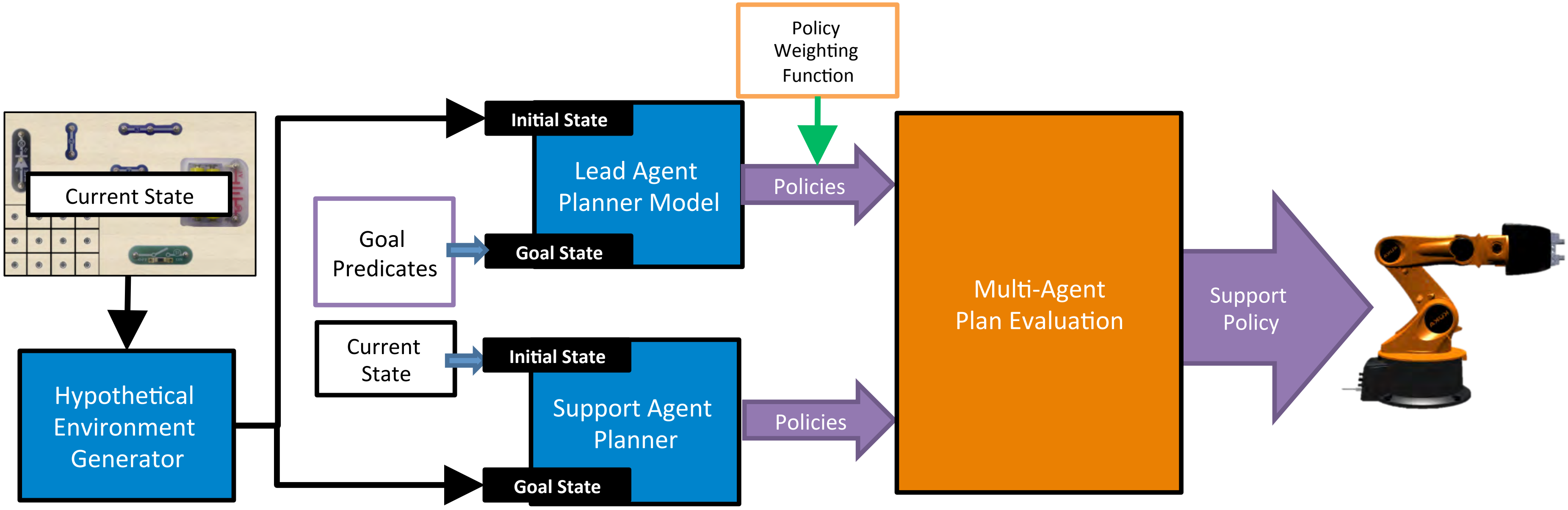
- “Construct a switched circuit with a power source and an LED”
- Many valid solutions
- Many suboptimal solutions exist
- Rigid, easily identified components

Application Domain: SnapCircuits



- Resource utilization
- Circuit board space utilization
- Role assignment
- Subtask parallelization

Supportive Behavior Planning



- Hypothesize future world states based on their plans
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Plan Evaluation

Choose the support policy (**ξ** ∈ **Ξ**) that minimizes the expected execution duration of the leader's policy (**π** ∈ **Π**) to solve the TAMP problem **T** from the current state ($\mathbf{s_c}$)

- Duration estimate must account for
  - Resource conflicts (shared utilization/demand)
  - Spatial constraints (support agent's avoidance of lead)

$$\min_{\xi \in \Xi} \sum_{\pi \in \Pi_T} w_\pi * \mathrm{duration}(T, \pi, \xi, s_c, \gamma)$$

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Weighting function makes a big difference!

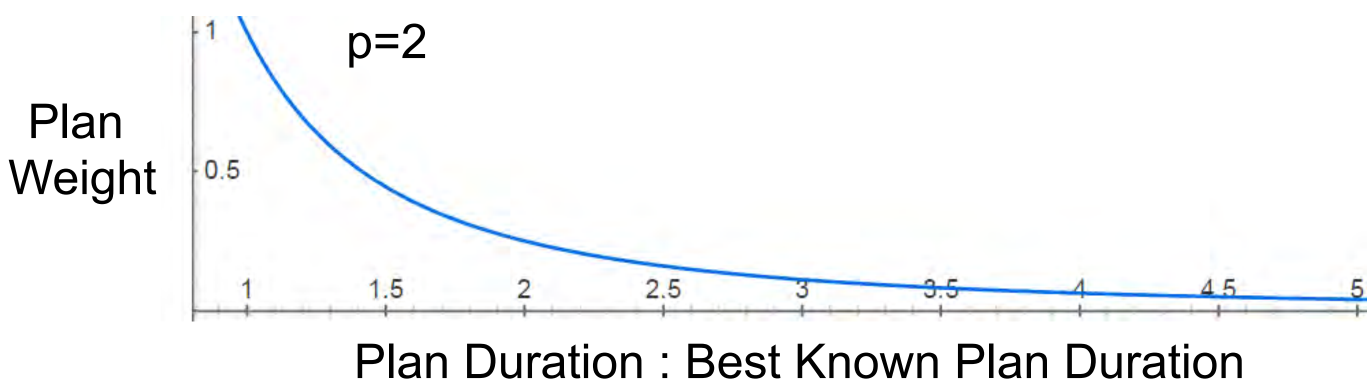
$$\min_{\xi \in \Xi} \sum_{\pi \in \Pi_T} w_\pi * \mathrm{duration}(T, \pi, \xi, s_c, \gamma)$$

Uniform Weighting Functions $w_\pi = 1$

Optimality-Proportional Weighting

$$w_\pi = \left(\frac{\min_{\pi \in \Pi_T} \text{duration}(T, \pi, \emptyset, s_0, f(x) = 1)}{\text{duration}(T, \pi, \emptyset, s_0, f(x) = 1)} \right)^{p}$$

Weight plans proportional to similarity vs. the best-known solution



Optimality-Proportional Weighting

Error Mitigation Weighting

$$w_\pi = \begin{cases} f(\pi) & ; \ \text{duration}(T, \pi, \emptyset, s_0, f(x) = 1) \leq \epsilon \\ -\alpha w_\pi & ; \ \text{otherwise} \end{cases}$$

Plans more optimal than some cutoff **ε** are treated normally, per *f*.

Suboptimal plans are negatively weighted, encouraging active mitigation behavior from the supportive robot.

$\alpha \leq \frac{1}{\max_\pi w_\pi}$ is a normalization term to avoid harm due to plan overlap

Error Mitigation Weighting

People who did all the work

Brad
Hayes

Alessandro
Roncone

Olivier
Mangin

Francesca
Stramandinoli

Thanks to...