Composable Causality in Semantic Robot Programming

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Introduction

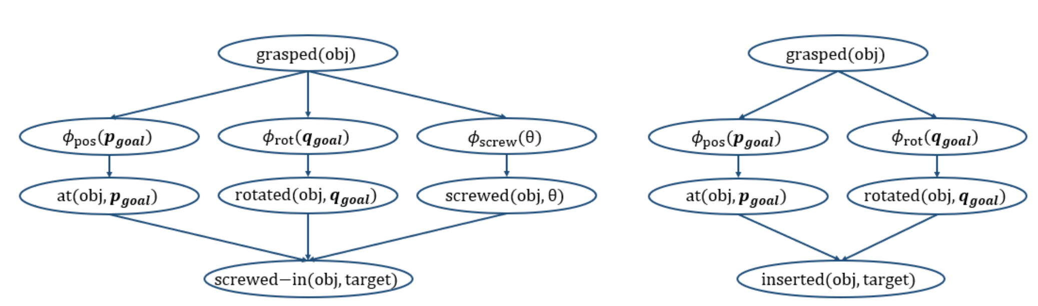
Assembly tasks present unique challenges in reasoning over objects, predicting the composed effects of actions, and executing complex behaviors in long-horizon tasks. *Object-centric controllers* [1] allow robots to achieve low-level motion primitives and can be *composed*—run concurrently with priorities between the behaviors—to perform *multi-objective actions* [2], such as those required in assembly tasks. Priorities between behaviors are generally hard-coded based on user experience, but we want robots to autonomously compose controller behaviors without relying on pre-defined priorities [3]. To autonomously compose controllers in long-horizon assembly tasks, the robot is given hierarchical causal information [4]. Our proposed *causal control basis* extends the intuitive declarative programming of the Semantic Robot Programming (SRP) paradigm [5] and allows the robot to autonomously predict the effects of multi-objective actions and achieve challenging goal-directed manipulation in furniture assembly tasks.

Causal Control Basis

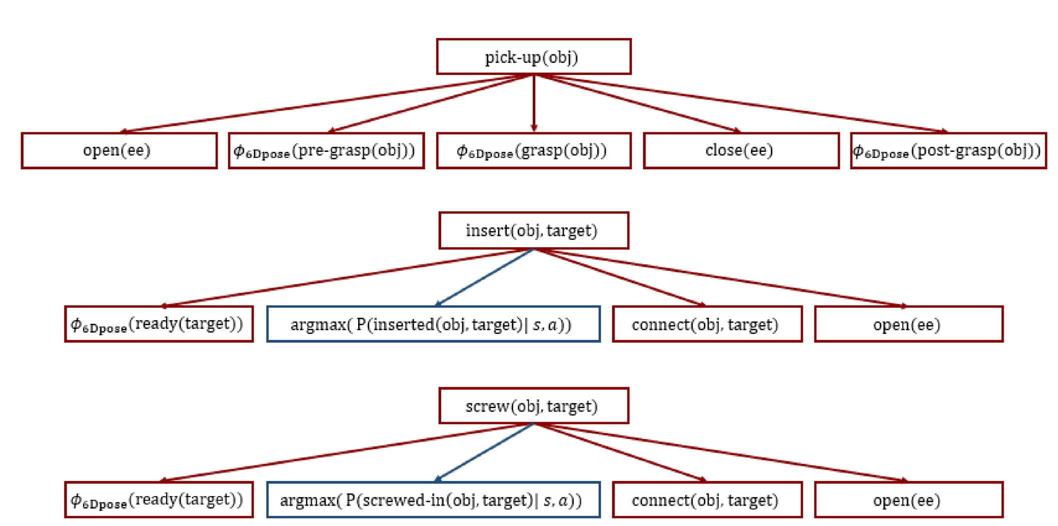
The *causal control basis* $\mathbf{\Phi} = (\Phi, G_C, G_T)$ is given to the robot and is comprised of:

- Controllers in the control basis Φ (pose, position, rotation, and screw controllers)
- Causal graphs G_C showing what controllers are involved in a multi-objective action
- Temporal graphs G_T showing the sequence of controllers that correspond to high-level symbolic actions

The robot will use the *causal control basis* to predict the composed effects of compositions of controllers and execute the composition most likely to achieve its composed effects.



Causal graphs for multi-objective *insert* and *screw* actions.



Temporal graphs for high-level actions.

Composed Causality Predictions

The *causal control basis* predicts the composed effects of a controller composition by estimating the transition probability of the composition based on a simulated execution of the action a and averaging across many executions:

$$a = \phi_k \lhd \phi_j \lhd \phi_i$$

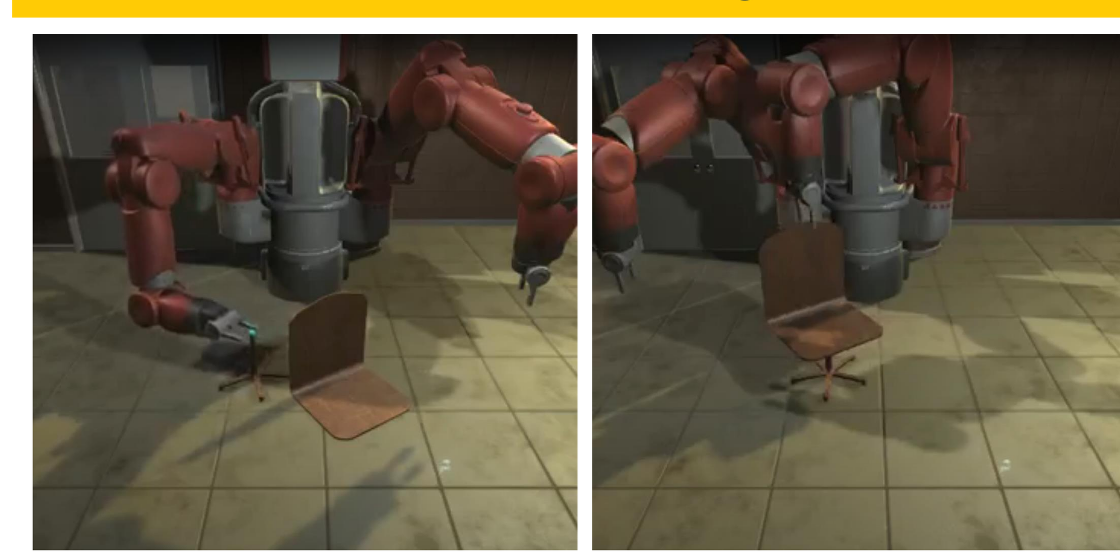
$$\hat{P}(s' \mid s, a) = \begin{cases} 1 & \text{objectives met} \\ 0 & \text{bad progress} \\ \frac{\phi_a(s) - \phi_a(s_T)}{\phi_a(s)} & \text{otherwise} \end{cases}$$

Composition a	Predicted Transition Probability $\hat{P}(s' \mid s, a)$
$\phi_{\text{pos}} \lhd \phi_{\text{rot}}$	**0.723**
$\phi_{\text{rot}} \lhd \phi_{\text{pos}}$	0.711

Composition a	Predicted Transition Probability $\hat{P}(s' \mid s, a)$
$\phi_{\text{rot}} \lhd \phi_{\text{screw}} \lhd \phi_{\text{pos}}$	**0.937**
$\phi_{\text{pos}} \lhd \phi_{\text{screw}} \lhd \phi_{\text{rot}}$	0.936
$\phi_{\text{screw}} \lhd \phi_{\text{pos}} \lhd \phi_{\text{rot}}$	0.929
$\phi_{\text{pos}} \lhd \phi_{\text{rot}} \lhd \phi_{\text{screw}}$	0.925
$\phi_{\text{screw}} \lhd \phi_{\text{rot}} \lhd \phi_{\text{pos}}$	0.923
$\phi_{\text{rot}} \lhd \phi_{\text{pos}} \lhd \phi_{\text{screw}}$	0.904

Transition probability predictions for *insert* (top) and *screw* (bottom) actions, based on 500 walkouts for each composition.

Multi-Objective Furniture Assembly Tasks



Chair assembly with multi-objective *insert* action. (action success rate 0.714; task success rate 1)

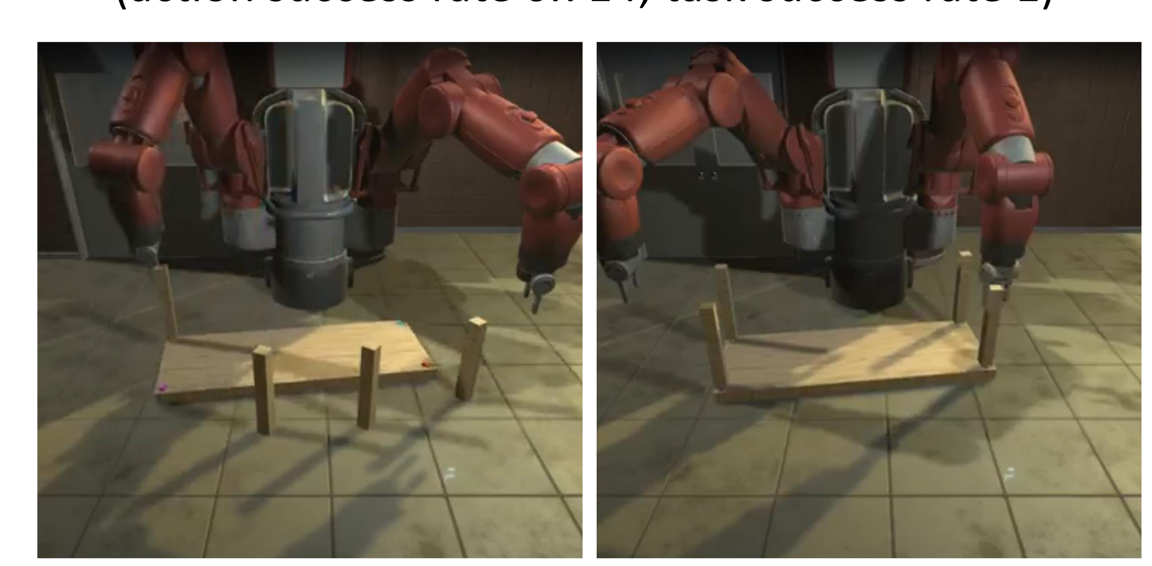


Table assembly with multi-objective *screw* action. (action success rate 0.923; task success rate 1)

We test our *causal control basis* in the IKEA Furniture Assembly Environment [6] simulator on the Baxter robot. The *causal control basis* uses its predictions to convert the output from an off-the-shelf task planner [7] into a sequence of (composed) controllers. The robot uses multi-objective *insert* and *screw* actions to successfully assemble a chair and a table in several random trials [8, 9]. Our work demonstrates that the proposed *causal control basis* accurately predicts the composed causality of multi-objective actions and provides the declarative knowledge necessary for robots to autonomously compose controllers.

References

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[8] Chair trial videos: https://www.youtube.com/watch?v=4Gpw7uuJju4
[9] Table trial videos: https://www.youtube.com/watch?v=63RFBU4dulo