# Reasoning about Actions for Planning in Robotics

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Sequential decision-making (SDM) plays a key role toward the development of artificial intelligence (AI) agents. SDM frequently requires the simultaneous capabilities of reasoning with world knowledge (including action knowledge) for state estimation, and planning to sequence actions toward maximizing long-term utilities. Although SDM requires both reasoning and planning capabilities, the study of the two problems has been largely separated within the AI community. We argue that:

> *Unified SDM frameworks that integrate both reasoning and planning paradigms are needed for the development of intelligent agents (robots in particular) that operate in the real world.*

On the one hand, knowledge representation and reasoning (KRR) focuses on developing declarative languages that are natural to humans, and (efficiently and robustly) drawing conclusions with the knowledge represented using these languages. Some of the KRR paradigms support representing and reasoning with not only logical, but also probabilistic knowledge. On the other hand, planning under uncertainty aims at computing policies that can be used for mapping the current state to an optimal action under the uncertainty in action outcomes.

iCORPP is a realization of integrating (both logical and probabilistic) reasoning and planning paradigms for robot sequential decision-making (Zhang *et al.* 2017). iCORPP uses P-log (Baral *et al.* 2009; Balai and Gelfond 2017) for KRR and Markov decision processes (MDP) for planning under uncertainty. iCORPP reasons about world dynamics (i.e., $Pr(s'|s,a)$) and dynamically construct task-oriented planners.

Consider the stacking example shown in Figure 1. There are a few objects of different shapes and sizes on a tabletop, and a robot gripper needs to stack them up in a single pile. The robot has only one type of actions, *move(A,B)*, for moving $A$ onto $B$, where $A$ is an object, and $B$ is either the tabletop or another object. Due to the different shapes and sizes, the robot has different success rates in grasping the objects. For instance, the robot has the knowledge that the success rates of grasping small objects of rectangle, trapezoid, and triangle are $0.8$, $0.7$, and $0.6$. If the object is large-sized, then the corresponding success rate is reduced by $50\%$.

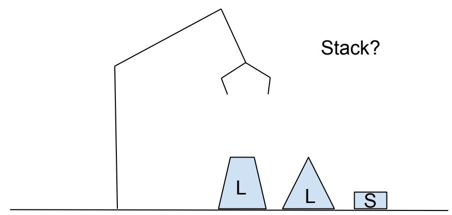


Figure 1: A stacking example for illustrating the need and mechanism of iCORPP.

One can easily build a probabilistic transition system, specifying the probability of an action leading the transition from one configuration to another. Using this transition system, SDM frameworks, such as MDP, can be used for computing an action policy. However, SDM frameworks are ill-equipped for incorporating declarative knowledge, e.g., large-sized objects make grasps more difficult.

iCORPP enables the robot to decompose this sequential decision-making task into two (relatively small) subtasks on reasoning and planning respectively. The reasoner (P-log based) reasons about contextual knowledge, such as how size and shape affect success rate (which is probabilistic), and one cannot place an object on top of a triangle (which is deterministic). The reasoner is not interested in solving the stacking problem, but focuses on computing the world dynamics for the probabilistic planner, where as the probabilistic planner (where size and shape are excluded) focuses on sequencing actions to accomplish the stacking goal.

The main objective of iCORPP is to decompose a robot planning problem into two sub-problems for reasoning and planning. Then a reasoner and a planner can be used to focus on the sub-problems of high-dimensional reasoning and long-horizon planning respectively (Zhang *et al.* 2017).

## References

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