Regularized Hierarchical Policies for Compositional Transfer in Robotics

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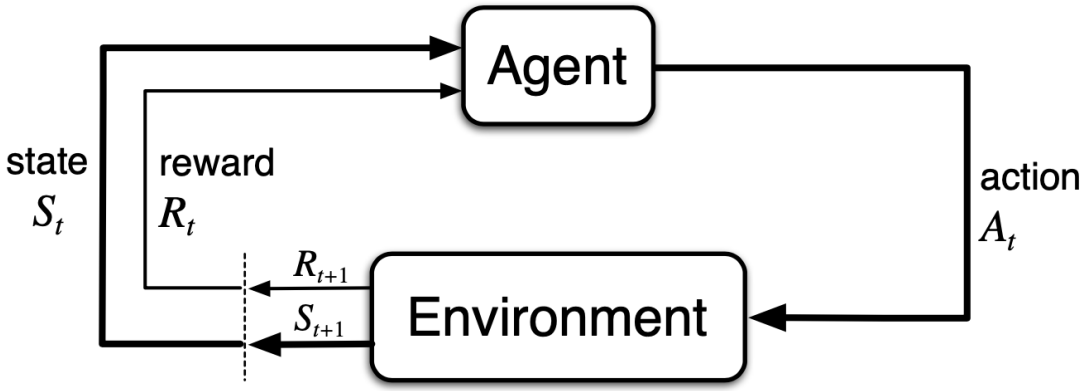
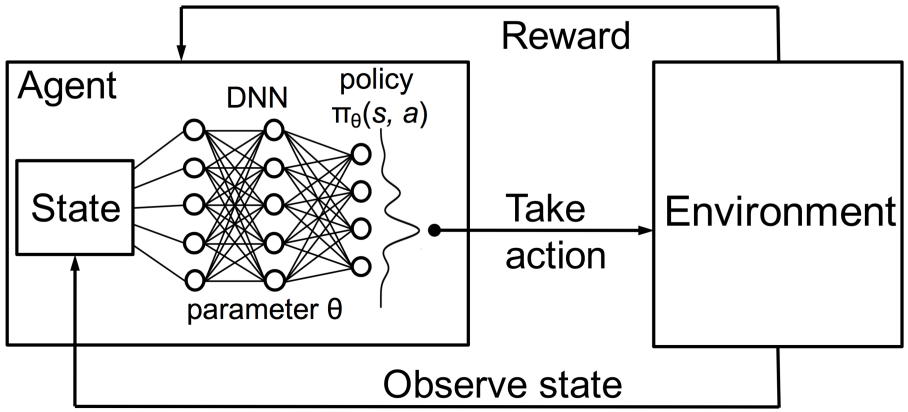
Reinforcement Learning



- Agent interacts with the environment at state $s_t \epsilon S$ by taking action $a_t \epsilon A$ according to policy $\pi(a_t|s_t)$
- Upon action from agent, environment state will transition to state s_{t+1} according to transition dynamics $p(s_{t+1}|s_t, a_t)$ and return a reward $r_t \epsilon R$
- Objective of reinforcement learning is to find the policy $\pi(a_t|s_t)$ so as to maximize the expected reward $V^{\pi}(s_0) = E_{\pi}[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t)]$

Value based RL

- Policy $\pi^{\theta}(s_t, a_t) = Q(s_t, a_t; \theta)$ predicts the expected reward of choosing a_t at state s_t
- Agent select action a_t with maximum expected reward
- After taking action a_t, environment transitions to s_{t+1} and gives reward r_t



- Parameters θ of policy $\pi^{\theta}(s_t, a_t)$ is adjusted to minimize the loss function $L(\theta) = (\hat{Q}(s_t, a_t) - Q(s_t, a_t; \theta))^2$

Policy based RL

- Policy based RL methods directly output the probability of taking an action instead of estimating the Q value
- Can be used for both continuous and discrete action space
- For continuous action space, mean and variance of a normal distribution is estimated and action is sampled from this distribution
- Common algorithms :- Policy Gradients and PPO

Regularized Hierarchical Policies

Policy

$$\pi_\theta(a|s,i) = \sum_{O=1}^{M} \pi_\theta^L(a|s,o)\pi_\theta^H(o|s,i) \tag{1}$$

Objective

$$\max_q J(q,\pi_{ref}) = E_{i\sim I}\left[E_{\pi,s\sim D}\left[\sum_{t=0}^{\infty}\gamma^t r_i(s_t,a_t)|s_{t+1}\sim p(.|_t,a_t)\right]\right] \tag{2}$$

subject to constraint

$$E_{s\sim D,i\sim I}\left[KL(q(.|s,i)||\pi_{ref}(.|s,i))\right] \leq \epsilon \tag{3}$$

Algorithm 1 Asynchronous Learner

Input: N_{steps} number of update steps, $N_{\text{targetUpdate}}$ update steps between target update, N_s number of action samples per state, KL regularization parameters ϵ, initial parameters for π, η and ϕ
initialize N = 0
while $k \leq N_{\text{steps}}$ **do**
  for k in $[0...N_{\text{targetUpdate}}]$ **do**
    sample a batch of trajectories τ from replay buffer B
    sample N_s actions from π_{θ_k} to estimate expectations below
    // compute mean gradients over batch for policy, Lagrangian multipliers and Q-function
    $\delta_\pi \leftarrow -\nabla_\theta \sum_{s_t \in \tau} \sum_{j=1}^{N_s} \exp\left(\frac{Q(s_t, a_j, i)}{\eta}\right) \log \pi_\theta(a_j | s_t, i)$ following Eq. 5
    $\delta_\eta \leftarrow \nabla_\eta g(\eta) = \nabla_\eta \eta\epsilon + \eta \sum_{s_t \in \tau} \log \frac{1}{N_s} \sum_{j=1}^{N_s} \exp\left(\frac{Q(s_t, a_j, i)}{\eta}\right)$ following Eq. 8
    $\delta_Q \leftarrow \nabla_\phi \sum_{i \sim I} \sum_{(s_t, a_t) \in \tau} \left(\hat{Q}_\phi(s_t, a_t, i) - Q^{\text{ret}}\right)^2$ with Q^{ret} following Eq. 6
    // apply gradient updates
    $\pi_{\theta_{k+1}}$ = optimizer_update(π, δ_π),
    η = optimizer_update(η, δ_η)
    $\hat{Q}_\phi$ = optimizer_update($\hat{Q}_\phi$, δ_Q)
    $k = k + 1$
  end for
  // update target networks
  $\pi' = \pi, Q' = Q$
end while

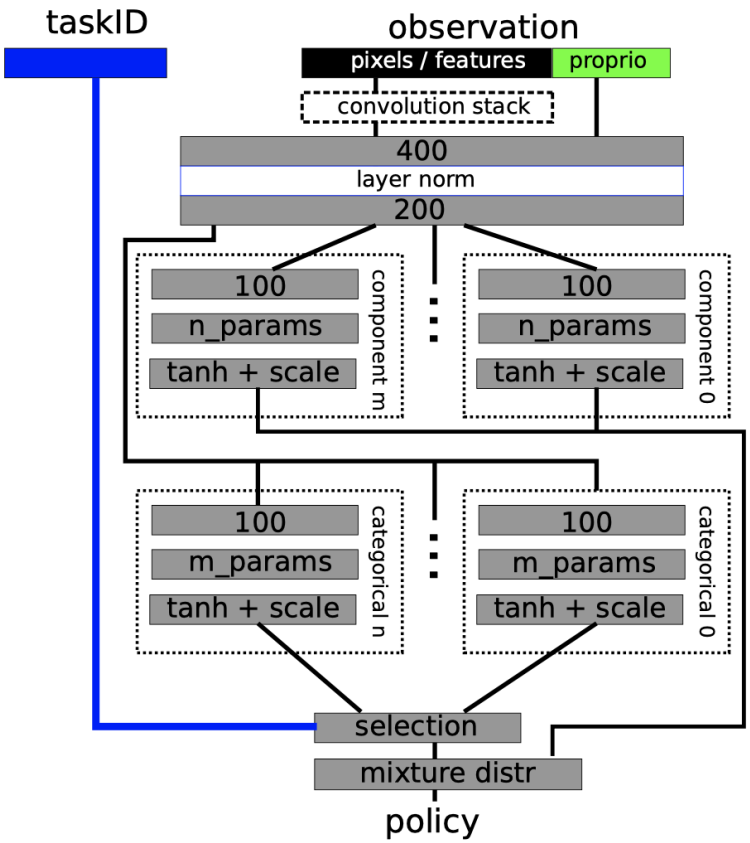
Algorithm 2 Asynchronous Actor

Input: $N_{\text{trajectories}}$ number of total trajectories requested, T steps per episode, ξ scheduling period
initialize N = 0
while $N < N_{\text{trajectories}}$ **do**
  fetch parameters θ
  // collect new trajectory from environment
  $\tau = \{\}$
  for t in $[0...T]$ **do**
    if $t \pmod{\xi} \equiv 0$ **then**
      // sample active task from uniform distribution
      $i_{act} \sim I$
    end if
    $a_t \sim \pi_\theta(\cdot|s_t, i_{act})$
    // execute action and determine rewards for all tasks
    $\bar{r} = [r_{i_1}(s_t, a_t), \ldots, r_{i_{|I|}}(s_t, a_t)]$
    $\tau \leftarrow \tau \cup \{(s_t, a_t, \bar{r}, \pi_\theta(a_0|s_t, i_{act}))\}$
  end for
  send batch trajectories τ to replay buffer
  $N = N + 1$
end while

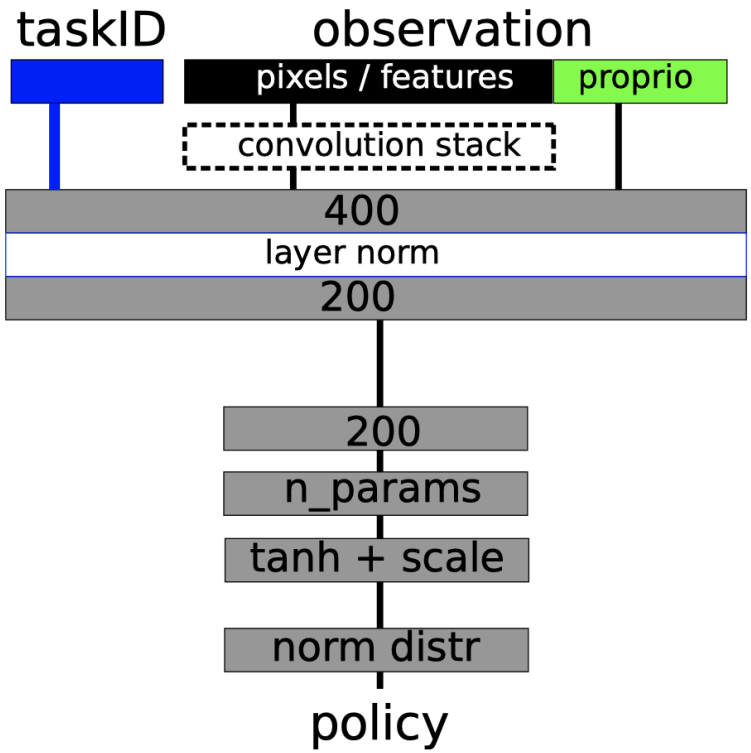
Regularized Hierarchical Policies

Architecture

RHPO architecture



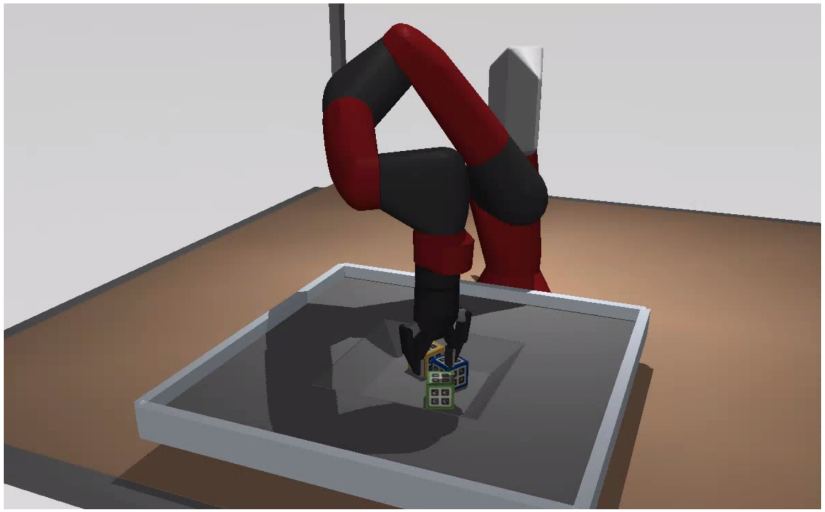
Monolithic architecture



Experiments

Exp 1 - Simulation - Setup

- 7DOF robot arm with parallel gripper
- Environment consists 3 cubes of colour yellow, blue and green with edge length 5cm
- Task is to place green cube over yellow cube

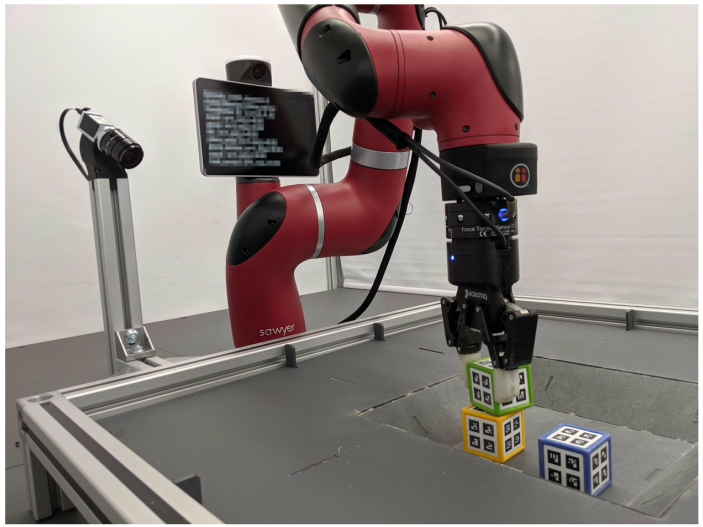


- Sub tasks are REACH(G), GRASP(G), LIFT(G), PLACE_WIDE(G,Y), PLACE_NARROW(G,Y), STACK(G,Y) and LEAVE(G,Y)
- Action space is $\{v_x, v_y, v_z, wrist_\omega, v_{finger}\}$
- Inputs are joint positions, velocities and torques, tool centre position, gripper motor position and velocity, binary grasp flag, wrist sensor force and torque readings and cube poses

Experiments

Exp 1 - Real robot - Setup

- Sawyer robot arm mounted on a table and equipped with a Robotiq 2F-85 parallel gripper.
- Three cameras on the basket track cubes to estimate their pose using Augmented Reality tags



- Environment setup, action space and inputs are same as simulation

Experiments

Exp 1 - Results

Figure: Real robot: Reach

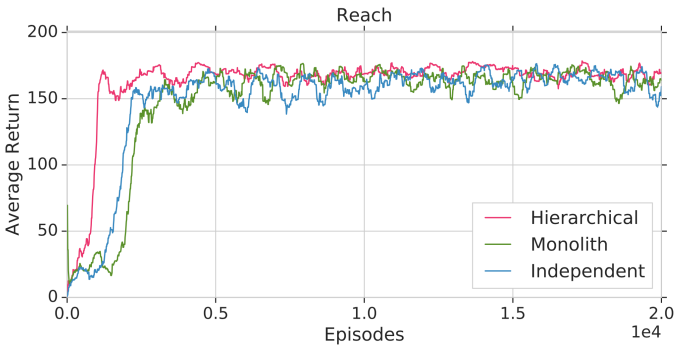


Figure: Real robot: Stack

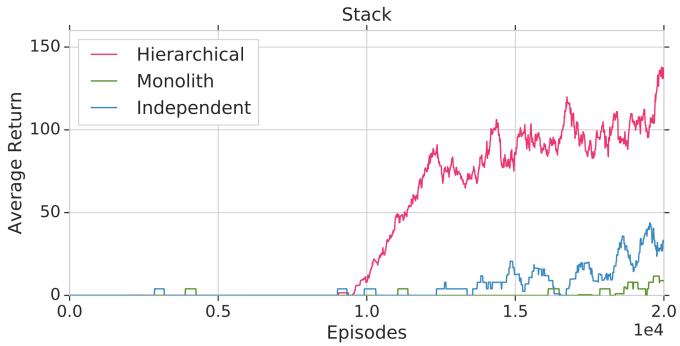
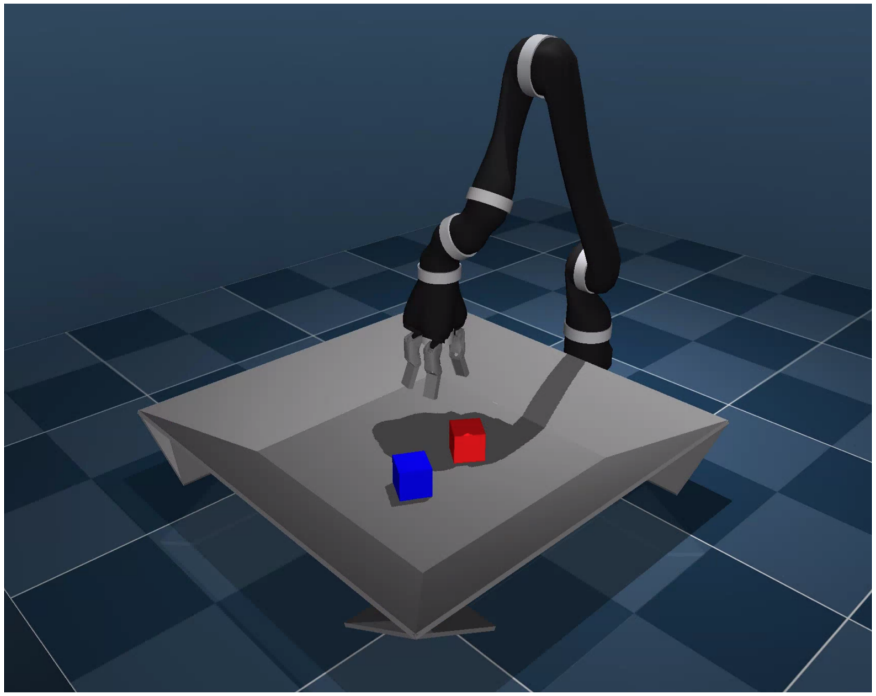


Figure: Simulation: Reach, Stack and Leave

Experiments

Exp 2 - Simulation - Setup

- Kinova Jaco robot arm, equipped with a Kinova KG-3 gripper
- Environment consists 2 cubes of colour red and blue with edge length 5cm
- Task is to place blue cube over red cube and then place red over blue cube



- Action space is

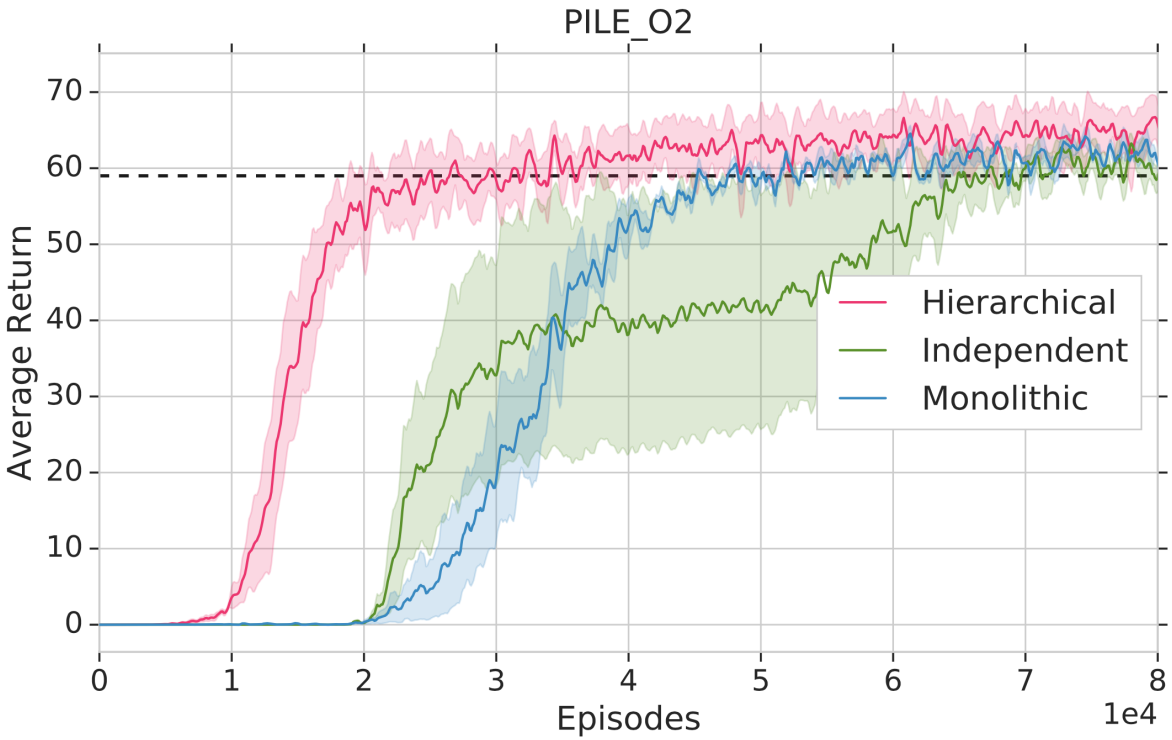
Entry	Dimension	Unit	Range
Joint velocity (Arm)	6	rad/s	[-0.8,0.8]
Joint velocity (Hand)	3	rad/s	[-0.8,0.8]

- Inputs are same as exp 1

Experiments

Exp 2 - Results

Figure: Simulation: Exp 2



Experiments

Exp 3 - Simulation - Setup

- Same robot setup as exp 2
- Environment same as exp 2 + box with movable lid that is closed initially
- Task is to clean up the scene by placing the cubes inside the box
- Action space is same as exp2
- Inputs are same as exp 2 + lid's angle and it's angular velocity

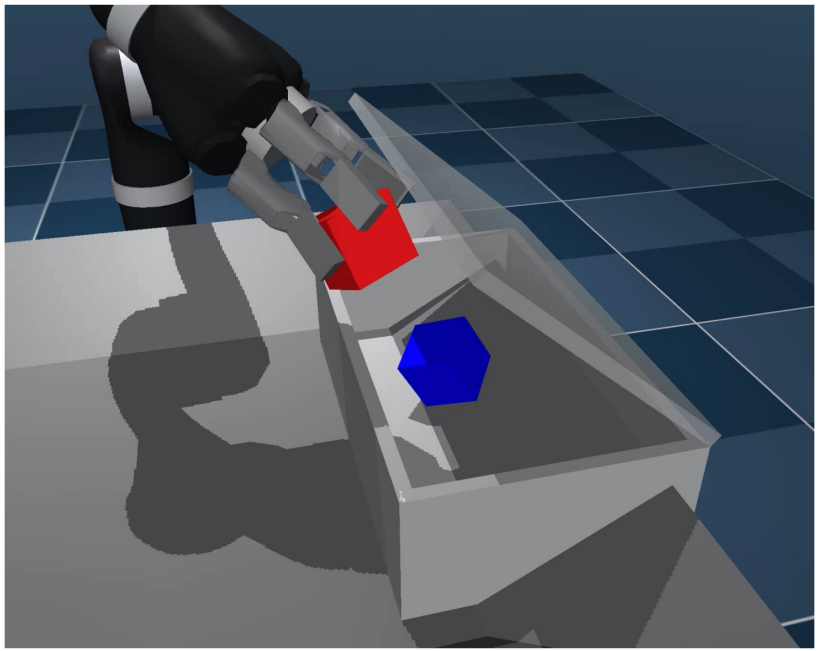
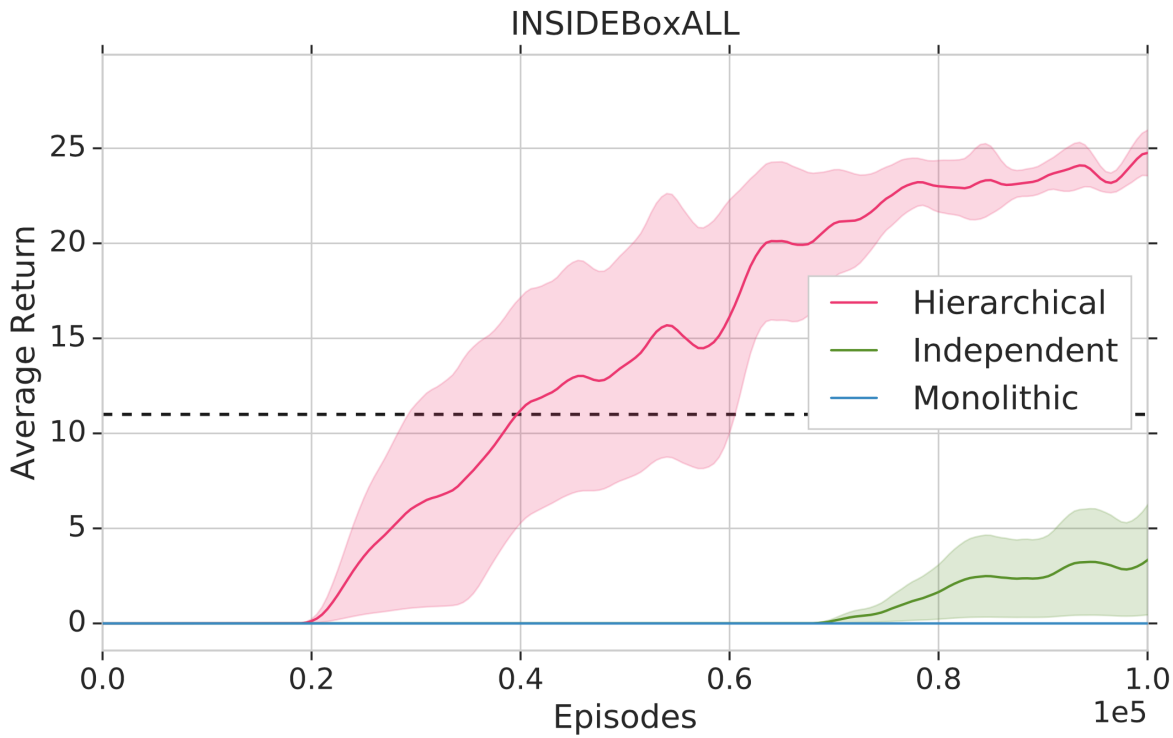


Figure: Simulation: Exp 3



Conclusions and future work

Conclusions

- In all experiments, both on simulated and real robot, RHPO outperforms baseline models that handle tasks independently or utilize implicit sharing
- Sample efficiency of RHPO is much higher compared to baseline models in complex tasks

Future work

- Evaluate with direct visual input
- Automatic task decomposition and sub task selection

References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Thank You!