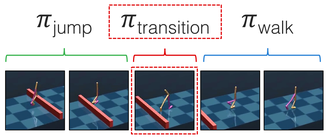


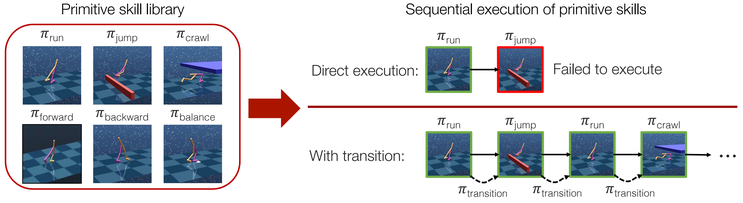
Composing Complex Skills by Learning Transition Policies

Youngwoon Lee* Shao-Hua Sun* Sriram Somasundaram Edward S. Hu Joseph J. Lim

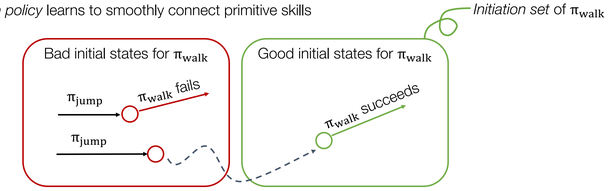
USC

Composing Complex Skills

- Primitive skills can be achieved by hard-coding, RL, and imitation learning
- We can compose a complex skill by sequentially executing primitive skills
- However, an ending state of a primitive skill may not be a good state to initiate the following skill



- A *transition policy* learns to smoothly connect primitive skills



Transition policy execution

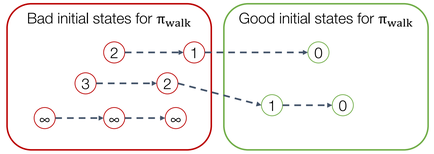
Proximity Reward

- A successful execution of a transition policy is defined by success of the following primitive skill
- The success/failure reward is too sparse to train a transition policy
- A *proximity predictor* learns to predict the proximity of a state to the initiation set

$$P(s) = \delta^{step(s)}$$

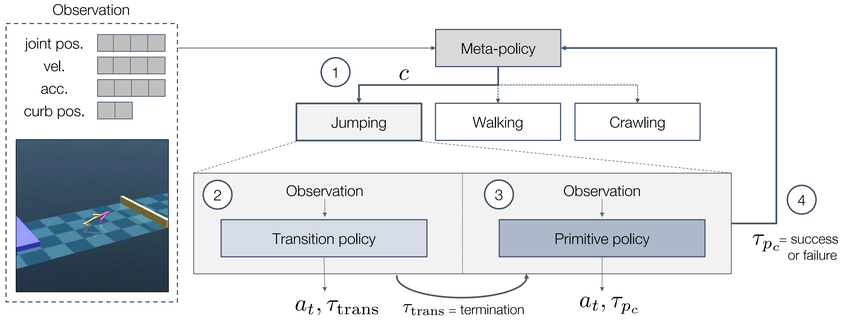
- We use the increase of predicted proximity to the initiation set as a dense reward

$$R_{\text{proximity}}(s_t, s_{t+1}) = P(s_{t+1}) - P(s_t)$$



The numbers inside the circles (states) represent transition steps to the initiation set

Modular Framework with Transition Policies



(1) The meta-policy chooses a primitive policy of index c
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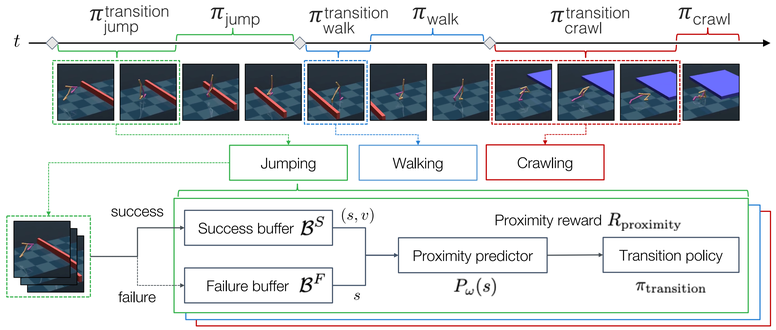
Training Transition Policies



Jointly train proximity predictors and transition policies by optimizing the following objectives:

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Baselines:
(1) TRPO, PPO: train a policy with a hand-engineered reward for 5x longer time
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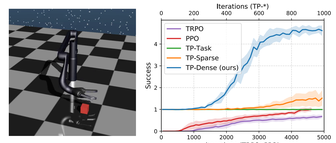
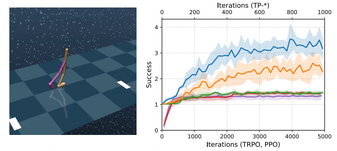
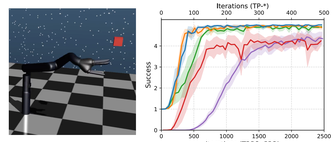
Dense reward
Sparse reward



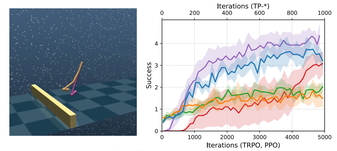
Repetitive picking up



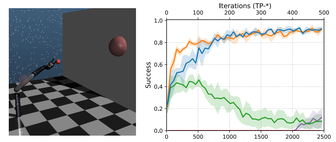
Patrol (Forward-Balance-Backward)



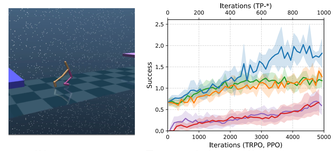
Repetitive catching



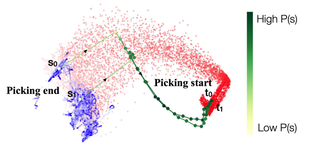
Hurdle (Forward-Jump)

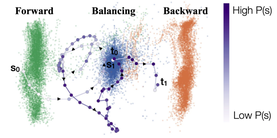


Serve (Toss-Hit)



Obstacle course (Forward-Jump-Crawl)





Transition trajectories of "Repetitive picking up" and "Patrol"

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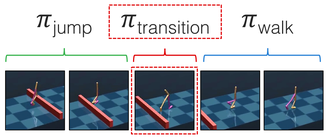

Composing Complex Skills by Learning Transition Policies

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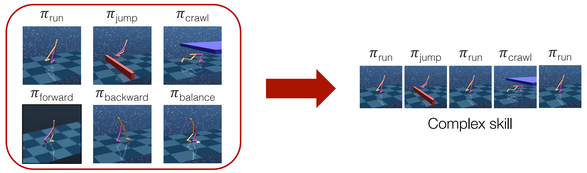
USC

Composing Complex Skills

- Compose a complex skill using primitive skills

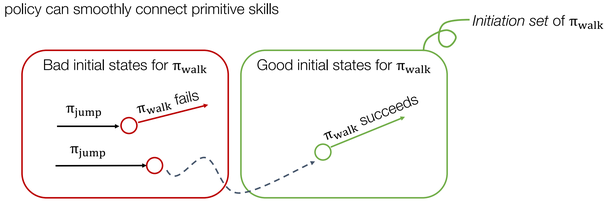


Primitive skill library

Complex skill

Transition Policy

- An ending state of a primitive skill may not be a good state to initiate the following skill
- A transition policy can smoothly connect primitive skills



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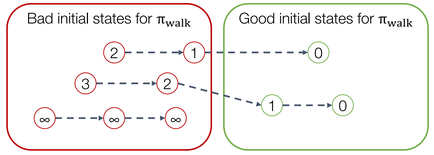

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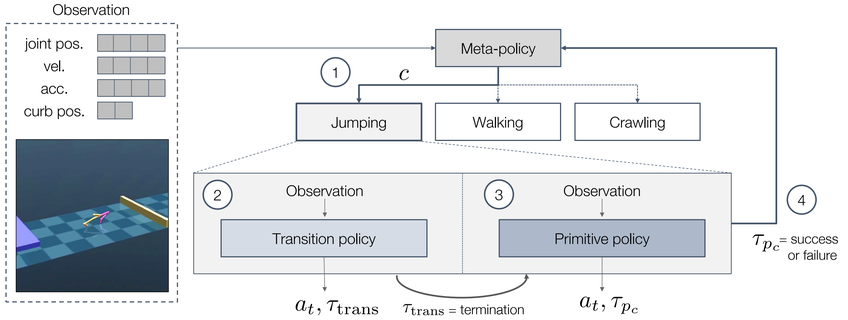
Modular Framework with Transition Policies



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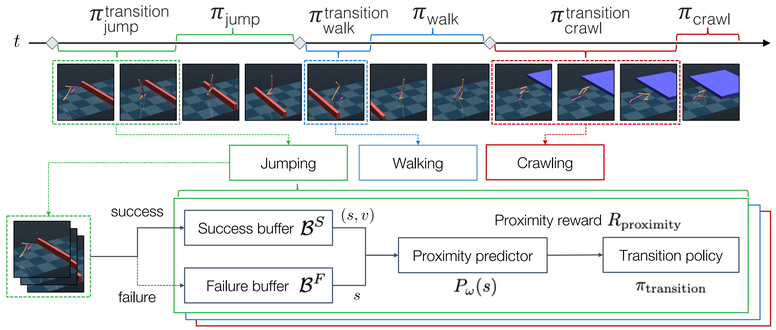
Training Transition Policies



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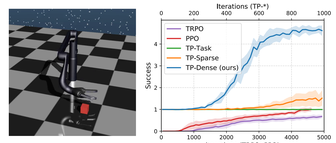
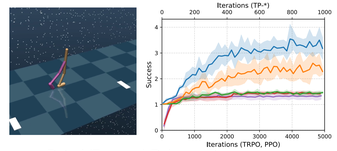
Sparse reward



Repetitive picking up



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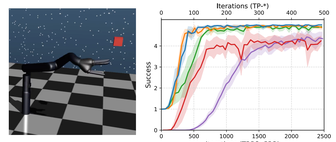
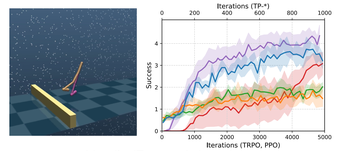


Repetitive catching



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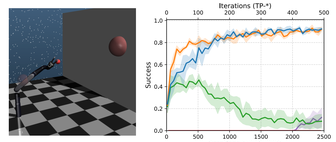

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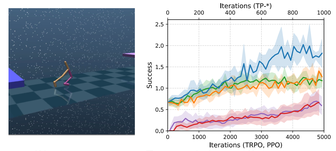

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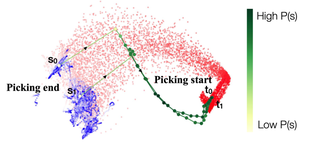

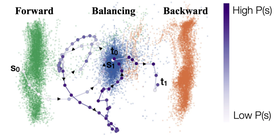

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Composing Complex Skills by Learning Transition Policies

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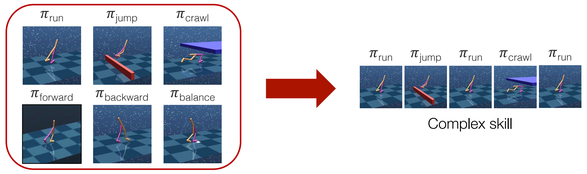
USC

Composing Complex Skills

- Learn complex hierarchical skills by exploiting previously learned skills



Transition Policy

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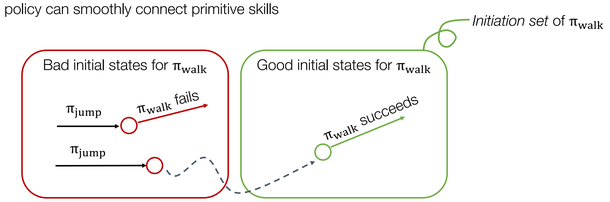

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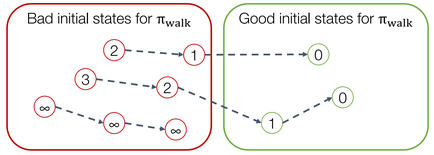

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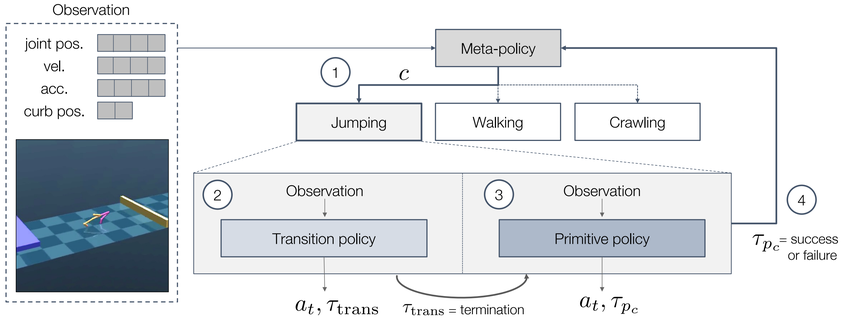
Modular Framework with Transition Policies



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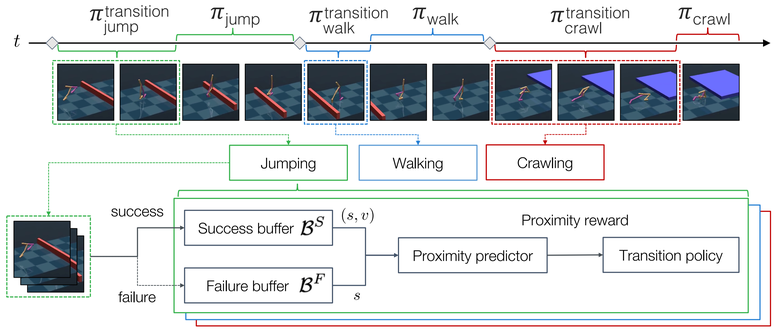

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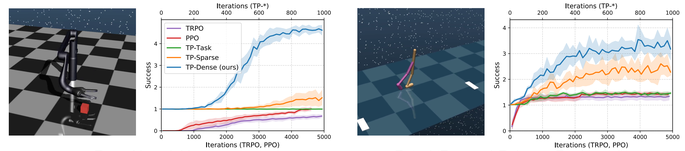

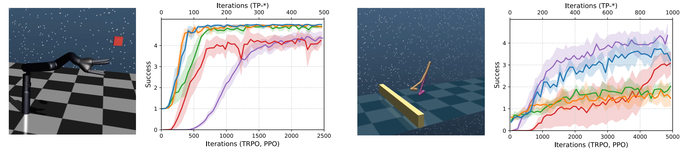

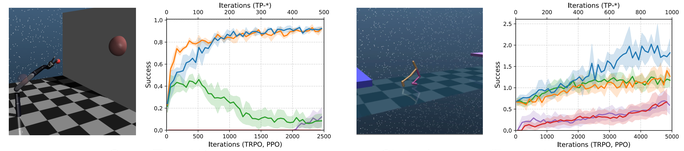

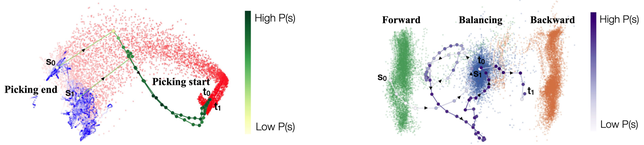

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Acknowledgement

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