Hindsight Experience Replay Practice Environment

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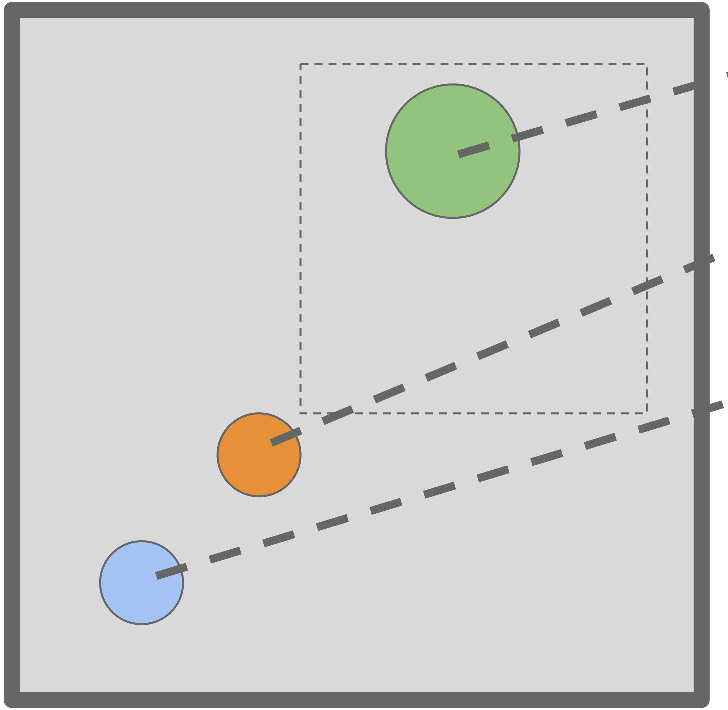
(10-703 Recitation Slides)

Environment (states)



Goal
(random initial location within boundary)
(does not move during episode)

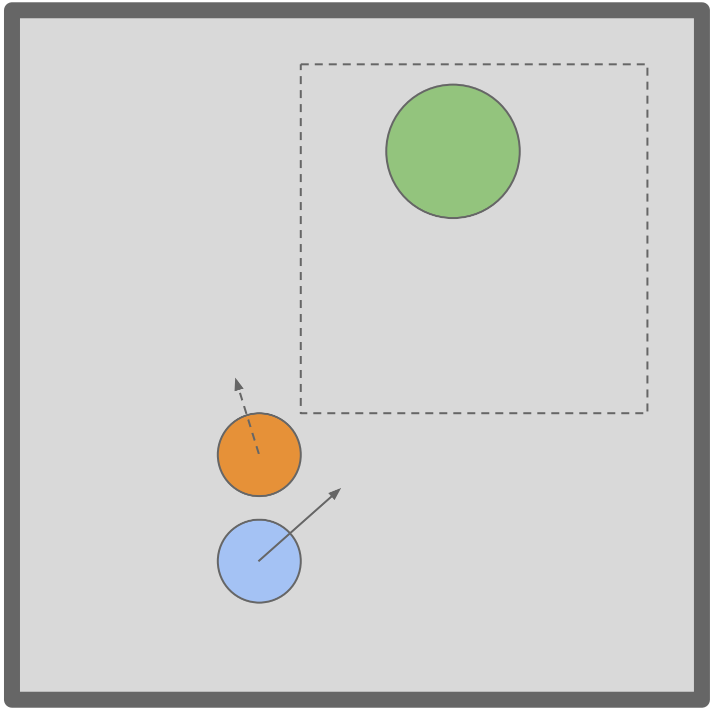
Box
(fixed initial position)
(can be pushed by pusher)

Pusher
(fixed initial position)
(directly controlled by agent)

Each state is of form:

$(X_{pusher}, Y_{pusher}, X_{box}, Y_{box}, X_{goal}, Y_{goal})$

Environment (transitions)

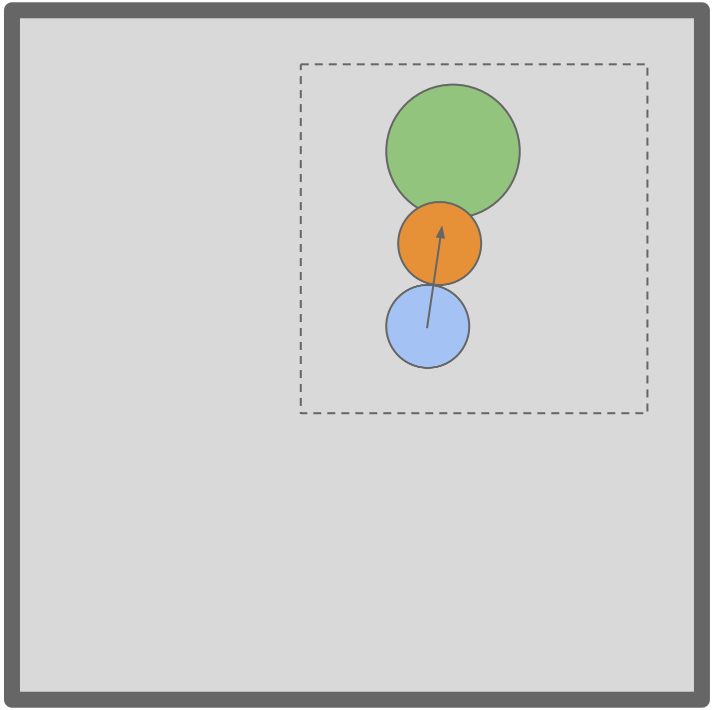


- Each action is of form:

$(X_{movement}, Y_{movement})$

- Moves pusher proportional to values
- Box moves if pusher collides with it

Environment (rewards)



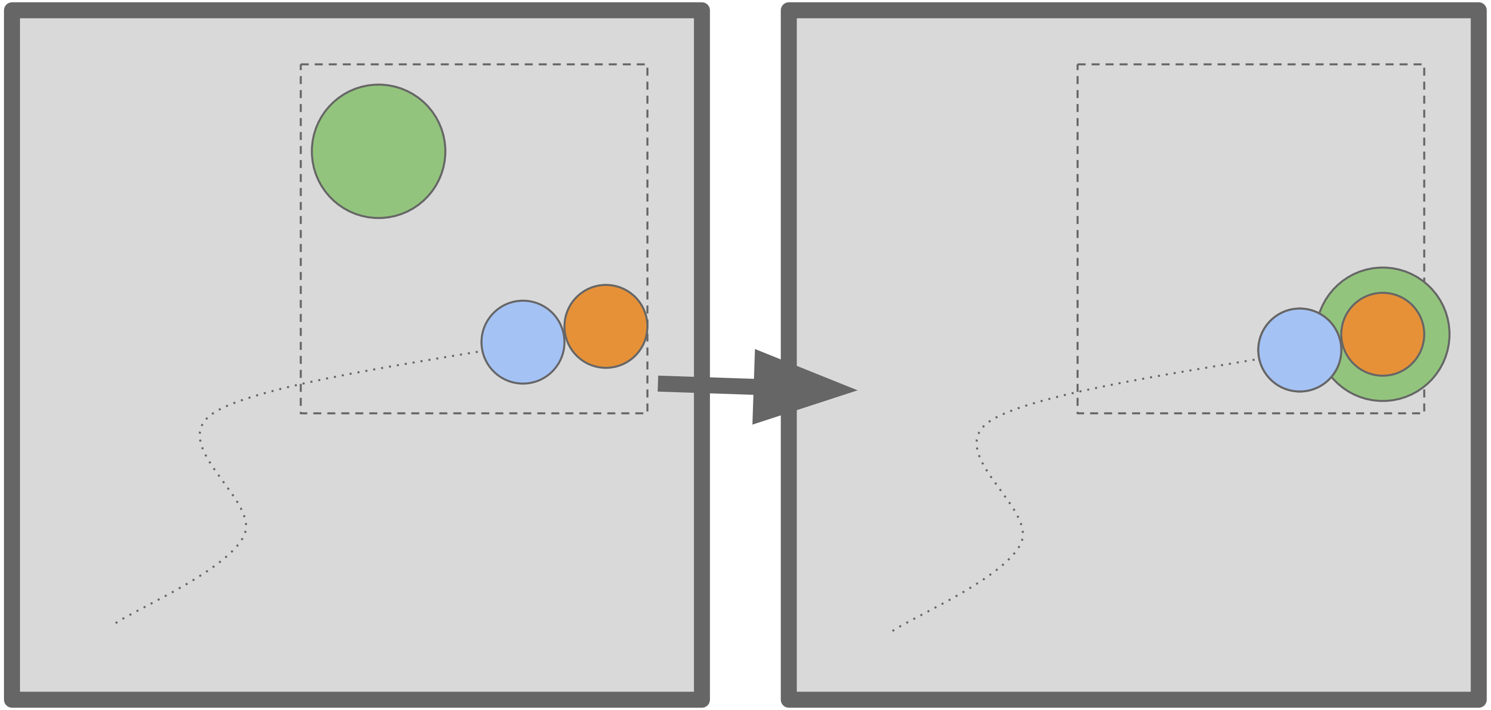
- Uniform reward for non-terminal step
  (living penalty of -1)
- Terminates if out of bounds
  (prorated negative reward)
- Terminates if box touches goal
  (0 reward)
- Also terminates after “max steps”
  (same -1 living penalty)

HER Motivation

- 2D Pusher environment has sparse reward
- Random actions rarely push box into goal
- As a result, most tuples have -1 reward (few “informative” tuples)

- Even though agent is not getting to goal, it is getting *somewhere*
- Could learn how to reach desired state of world from arbitrary reached states
- Main idea: Create new trajectory with new goal which is reached in trajectory

HER Intuition



HER Pseudocode (1)

Algorithm 1 Hindsight Experience Replay (HER)

Given:

- an off-policy RL algorithm $\mathbb{A}$, ▷ e.g. DQN, DDPG, NAF, SDQN
- a strategy $\mathbb{S}$ for sampling goals for replay, ▷ e.g. $\mathbb{S}(s_0, \ldots, s_T) = m(s_T)$
- a reward function $r : \mathcal{S} \times \mathcal{A} \times \mathcal{G} \to \mathbb{R}$. ▷ e.g. $r(s, a, g) = -[f_g(s) = 0]$

Initialize $\mathbb{A}$ ▷ e.g. initialize neural networks
Initialize replay buffer R
for episode $= 1, M$ **do**

Standard DRL

    Sample a goal g and an initial state s_0.
    for $t = 0, T-1$ **do**
        Sample an action a_t using the behavioral policy from $\mathbb{A}$:
$$a_t \leftarrow \pi_b(s_t || g)$$ ▷ || denotes concatenation
        Execute the action a_t and observe a new state s_{t+1}
    end for

HER Pseudocode (2)

for $t = 0, T-1$ **do**
    $r_t := r(s_t, a_t, g)$
    Store the transition $(s_t||g, a_t, r_t, s_{t+1}||g)$ in R ▷ standard experience replay
    Sample a set of additional goals for replay $G := \mathbb{S}(\textbf{current episode})$
    for $g' \in G$ **do**
        $r' := r(s_t, a_t, g')$
        Store the transition $(s_t||g', a_t, r', s_{t+1}||g')$ in R ▷ HER
    end for
end for
for $t = 1, N$ **do**
    Sample a minibatch B from the replay buffer R
    Perform one step of optimization using $\mathbb{A}$ and minibatch B
end for
end for

Core HER procedure

Implementation (provided code)

```
#returns list of new states and list of new rewards for use with HER
def apply_hindsight(self, states, actions, goal_state):
        goal = goal_state[2:4] #get new goal location (last location of box)
        states.append(goal_state)
        num_tuples = len(actions)
        her_states, her_rewards = [], []
        states[0][-2:] = goal.copy()
        her_states.append(states[0])
        #for each state, adjust goal and calculate reward obtained
        for i in range(1, num_tuples + 1):
                state = states[i]
                state[-2:] = goal.copy()
                reward = self._HER_calc_reward(state)
                her_states.append(state)
                her_rewards.append(reward)
        return her_states, her_rewards
```

Implementation (standard loop)

```
action, q = agent.pi(obs, apply_noise=True, compute_Q=True)
assert action.shape == env.action_space.shape

new_obs, r, done, info = env.step(max_action * action)
t += 1
episode_reward += r
episode_step += 1
agent.store_transition(obs, action, r, new_obs, done)

# storing info for hindsight
if kwargs["her"]:
        states.append(obs.copy())
        actions.append(action.copy())

obs = new_obs

if done:
        [...]
```

Implementation (HER change)

```
[...]
if done:
    if kwargs["her"]:
        # create hindsight experience replay
        her_states, her_rewards =
            env.env.apply_hindsight(states, actions, new_obs.copy())

        # store her transitions: her_states: n+1, her_rewards: n
        for her_i in range(len(her_states)-1):
            agent.store_transition(her_states[her_i], actions[her_i],
                her_rewards[her_i], her_states[her_i+1],
                her_rewards[her_i] == 0)
    [perform memory replay]
```

Parameters

- We used OpenAI Baselines DDPG
- Batch size = 128
- Gamma = 0.98
- Learning rate (actor) = 1e-4
- Learning rate (critic) = 1e-3
- Noise = epsilon normal action noise (0.01, 0.2)
- Architecture (actor and critic) = 3 hidden layers each, 64 nodes each
- Num actors = 8
- Max rollout steps = 320

Comparison Plots