强化学习原理及应用
Reinforcement Learning (RL): Theories & Applications

DCS6289 Spring 2022

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Lecture 14：Hierarchical RL

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Hierarchical RL

- Why Hierarchical Approaches?
  - To deal with the problem of sparse reward
  - To solve the sequential decision-making problem with long horizon
  - Many large problems have hierarchical structure that allows them to be broken down into sub-problems. The sub-problems, being smaller, are often solved more easily

- What is key of Hierarchical RL?
  - Temporally extended actions
  - Policy on the abstract action and policy in the abstract action

Hierarchical RL

Basic model – Two levels of hierarchy

- High level:
  - High level policy: $g_t = \pi^h(s_t)$
  - The high level policy receives state s_t, then chooses an abstracted action $g_t \in G$, where G denotes the set of all possible current abstracted actions (e.g., skills/sub-policies/options/goals)
  - The high level aims to maximize the rewards from environment directly, i.e., extrinsic rewards

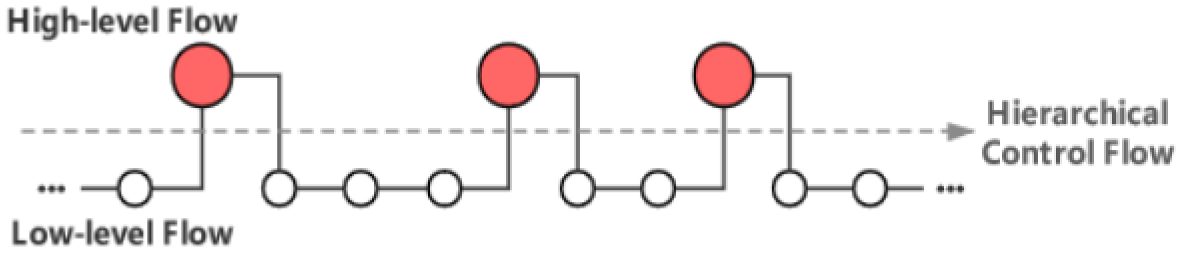
- Low level:
  - Low level policy: $a_t = \pi^l(s_t, g_t)$
  - The low level policy receives state s_t and g_t then takes a primitive action a_t, while results in a new state s_{t+1}
  - The low level is expected to accomplish subtasks or achieve goals from high level

Hierarchical RL

Basic model – Two levels of hierarchy

- Both high level and low level can use RL algorithms to realize (e.g. DQN, PPO, DDPG, TD3)
- The hierarchy can be deeper (i.e., more than 2 levels)

$$g_t = \pi^h(s_t)$$



$$a_t = \pi^l(s_t, g_t)$$

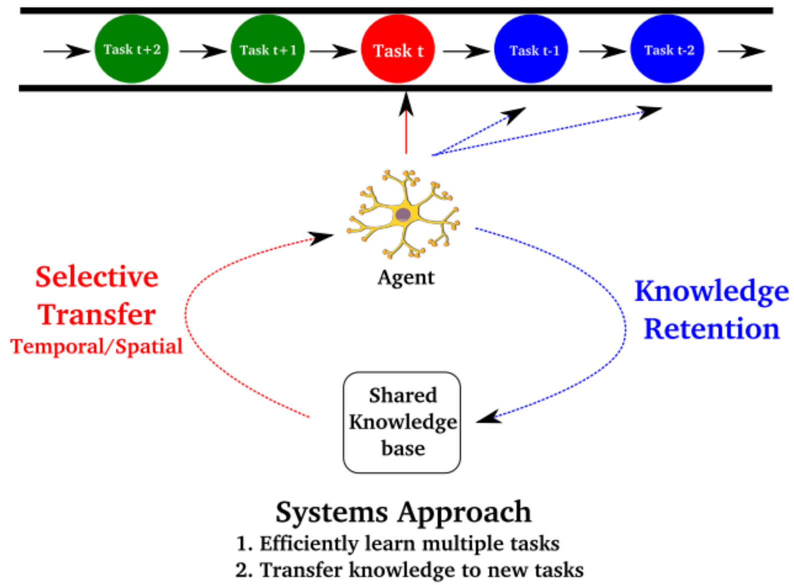
Hierarchical RL

- Discrete abstracted action
  - H-DRLN
  - OC
- Continual abstracted action
  - FuN
  - HIRO

Hierarchical RL

H-DRLN

- Motivation
  - In Minecraft, the task of building a wooden house can be decomposed into sub-tasks (a.k.a skills) such as chopping trees, sanding the wood, cutting the wood into boards and finally nailing the boards together.
  - The knowledge gained from 'building a house' task can also be partially reused when building a small city
- Main idea
  - Predefined and reusable skills

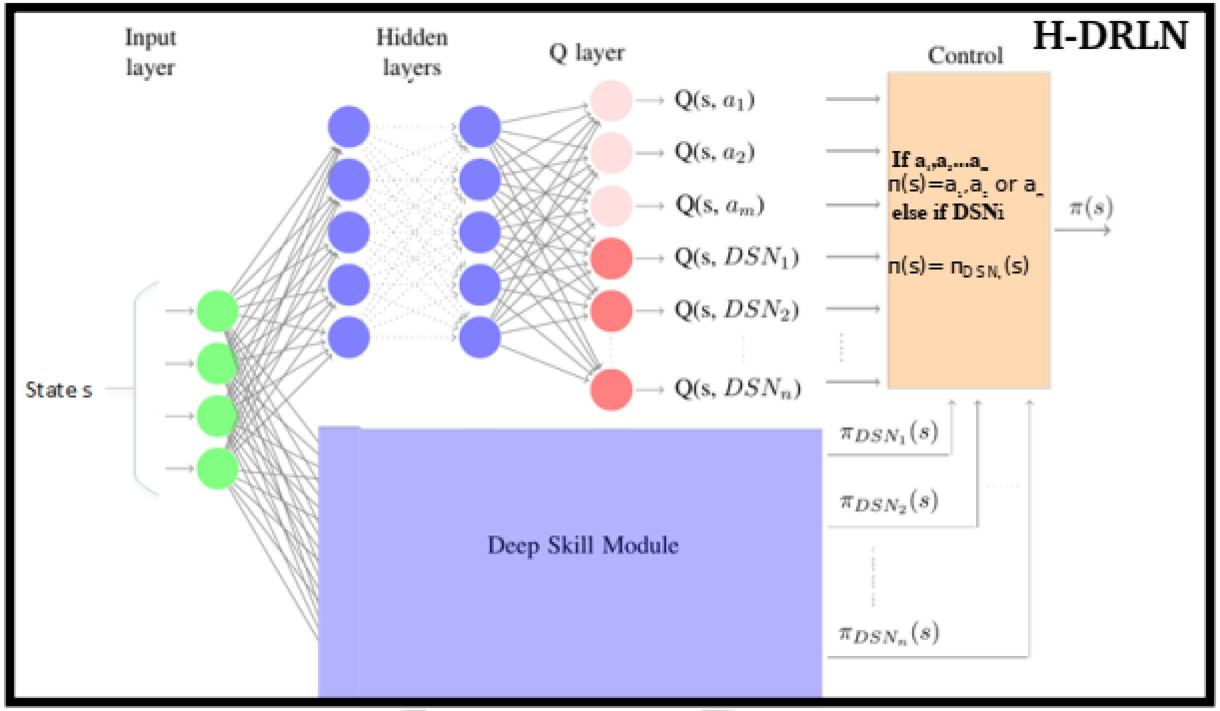


Tessler, Chen, et al. "A Deep Hierarchical Approach to Lifelong Learning in Minecraft". *Proceedings of the AAAI Conference on Artificial Intelligence* 31(2017).

Hierarchical RL

H-DRLN

- The outputs of the H-DRLN consist of primitive actions as well as skills. The H-DRLN learns a policy that determines when to execute primitive actions and when to reuse pre-learned skills.



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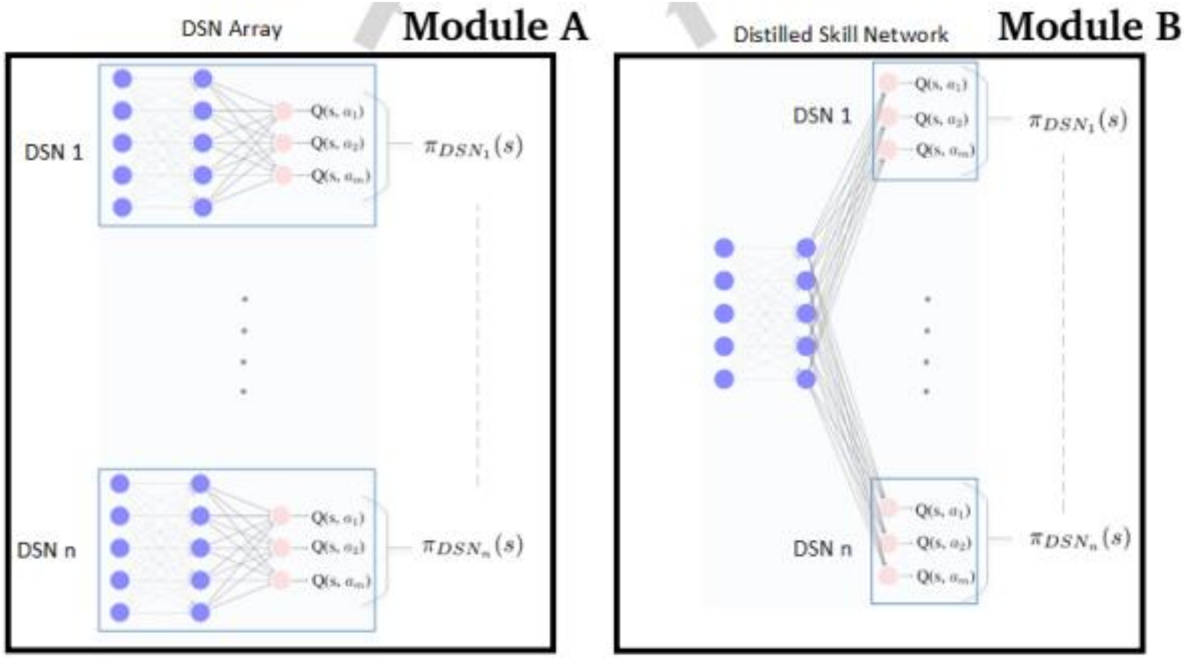
Hierarchical RL

H-DRLN

- The architecture of the deep skill module can be either a DSN array or a Distilled Multi-Skill Network.



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Hierarchical RL

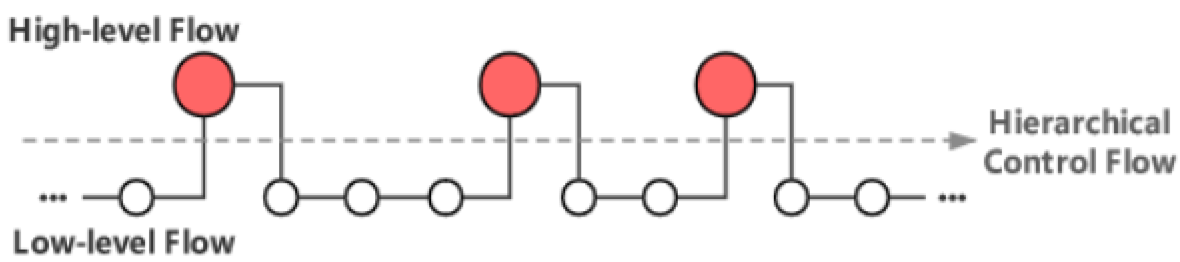
The training process of H-DRLN

- High level:
  - For a skill σ_t initiated in state s_t at time t that has executed for a duration k, the H-DRLN target function is given by:

$$y_t = \begin{cases} \sum_{j=0}^{k-1} \left[\gamma^j r_{j+t}\right] & \text{if } s_{t+k} \text{ terminal} \\ \sum_{j=0}^{k-1} \left[\gamma^j r_{j+t}\right] + \gamma^k \max_{\sigma'} Q_{\theta_{target}} \left(s_{t+k}, \sigma'\right) & \text{else} \end{cases}$$

  - Transition tuple $(s_t, \sigma_t, \sum_{j=0}^{k-1} \gamma^j r_{t+j}, s_{t+k})$

- Low level:
  - Pre-trained with manually defined scenarios



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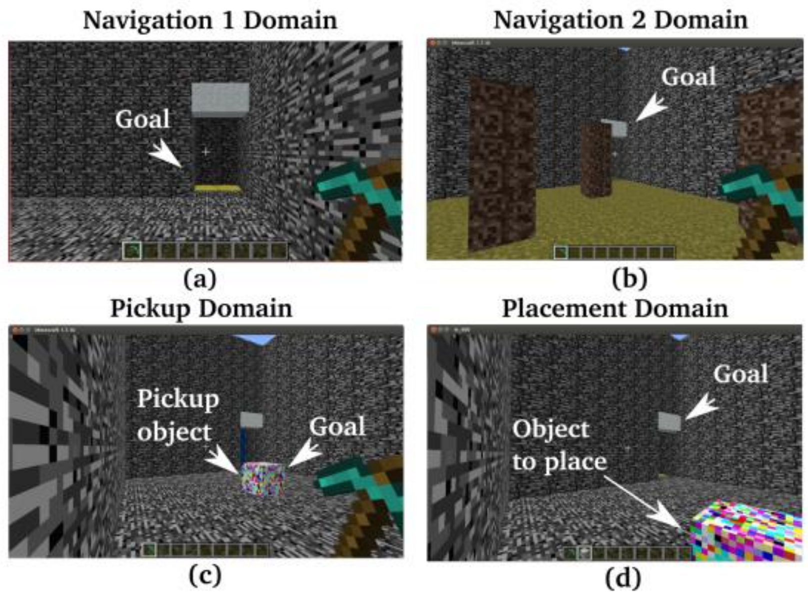
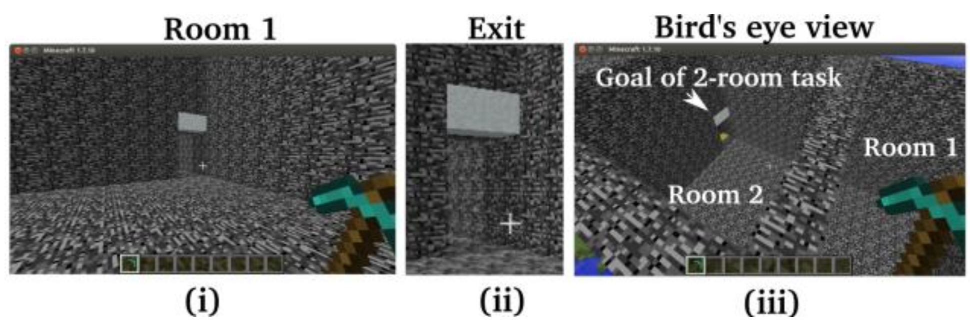
Hierarchical RL

H-DRLN

- Experiments
  - The manually defined scenarios:



  - The Two-room scenario:

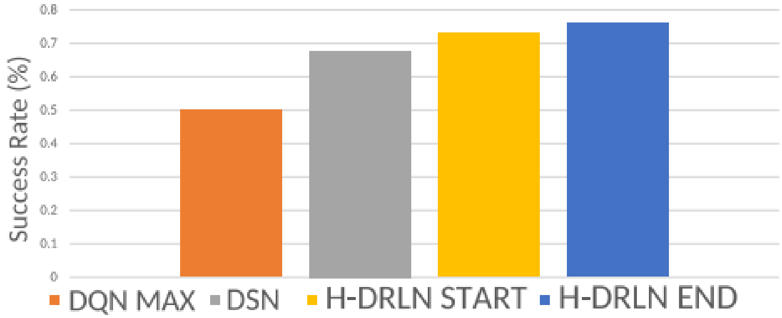


Tessler, Chen, et al. "A Deep Hierarchical Approach to Lifelong Learning in Minecraft". *Proceedings of the AAAI Conference on Artificial Intelligence* 31(2017).

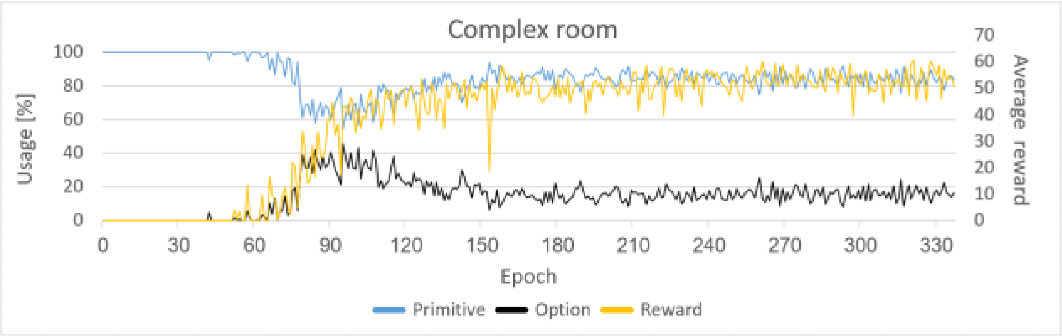
Hierarchical RL

H-DRLN

- Experiments
  - The success percentages of the two-room scenario



  - Information in the training process



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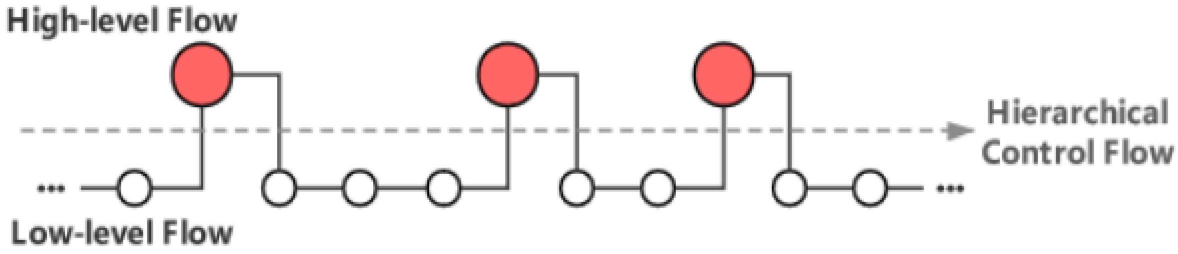
Hierarchical RL

OC

- Motivation
  - Create temporally extended actions autonomously
  - No additional rewards or subgoals are required
- Method
  - Using differentiable parameterized function approximators
    - policy over options π_{Ω}
    - intra-option policy $\pi_{W,\theta}$ for option W
    - Termination policy $\beta_{\mathrm{W},\vartheta}$ for option W
  - Calculate the derivative of the cumulative return reward function with respect to the parameters



Bacon, Pierre-Luc, et al. "The Option-Critic Architecture". *Proceedings of the AAAI Conference on Artificial Intelligence* 31(2017).

Hierarchical RL

OC

- Define the option-value function

$$Q_\Omega(s,\omega) = \sum_a \pi_{\omega,\theta}(a \mid s)\, Q_U(s,\omega,a)$$

- Where $Q_U: S \times \Omega \times A \rightarrow R$ is the value of executing an action in the context of a state-option pair:

$$Q_U(s,\omega,a) = r(s,a) + \gamma \sum_{s'} \mathrm{P}(s' \mid s,a)\, U(\omega,s')$$

- The function $U: \Omega \times S \rightarrow R$ is called the option-value function upon arrival

$$U(\omega,s') = (1-\beta_{\omega,\vartheta}(s'))Q_\Omega(s',\omega) + \beta_{\omega,\vartheta}(s')V_\Omega(s')$$

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Hierarchical RL

OC

- Theorem 1 (Intra-Option Policy Gradient Theorem). Given a set of Markov options with stochastic intra-option policies differentiable in their parameters θ, the gradient of the expected discounted return with respect to θ and initial condition (s_0, w_0) is:

$$\sum_{s,\omega} \mu_\Omega(s, \omega \mid s_0, \omega_0) \sum_a \frac{\partial \pi_{\omega,\theta}(a \mid s)}{\partial \theta} Q_U(s, \omega, a)$$

- Theorem 2 (Termination Gradient Theorem). Given a set of Markov options with stochastic termination functions differentiable in their parameters ϑ, the gradient of the expected discounted return objective with respect to ϑ and the initial condition (s_1, w_0) is:

$$-\sum_{s',\omega} \mu_\Omega(s', \omega \mid s_1, \omega_0) \frac{\partial \beta_{\omega,\vartheta}(s')}{\partial \vartheta} A_\Omega(s', \omega)$$

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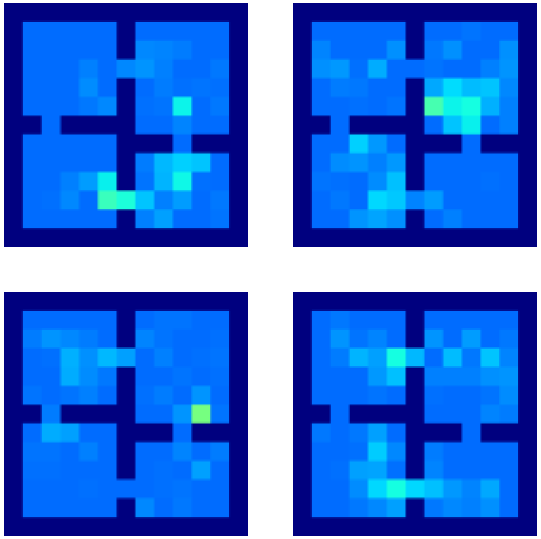
Hierarchical RL

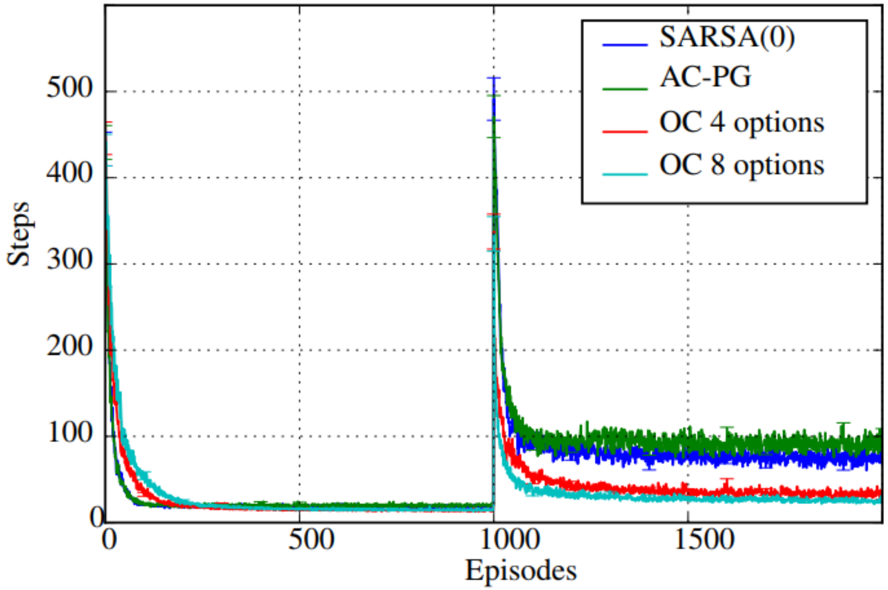
OC

- four-rooms domain

Termination probabilities for the option-critic agent learning with 4 options



After a 1000 episodes, the goal location in the four-rooms domain is moved randomly



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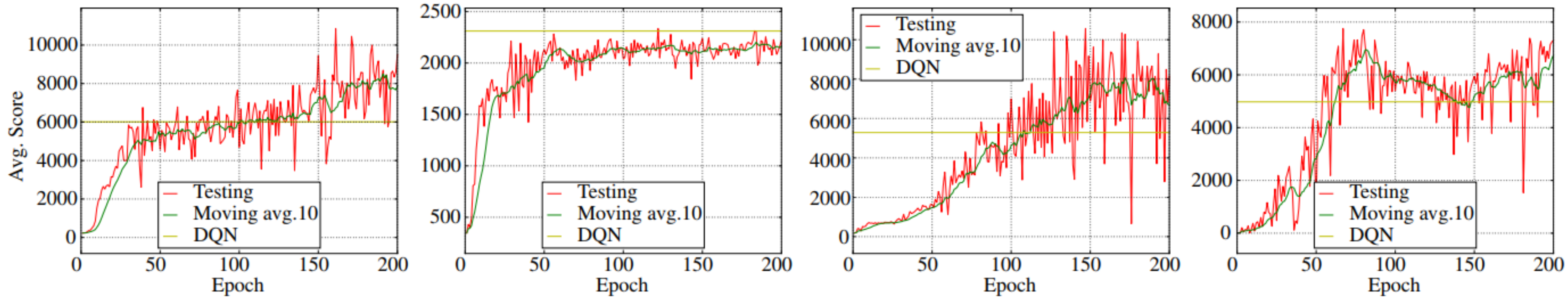
Hierarchical RL

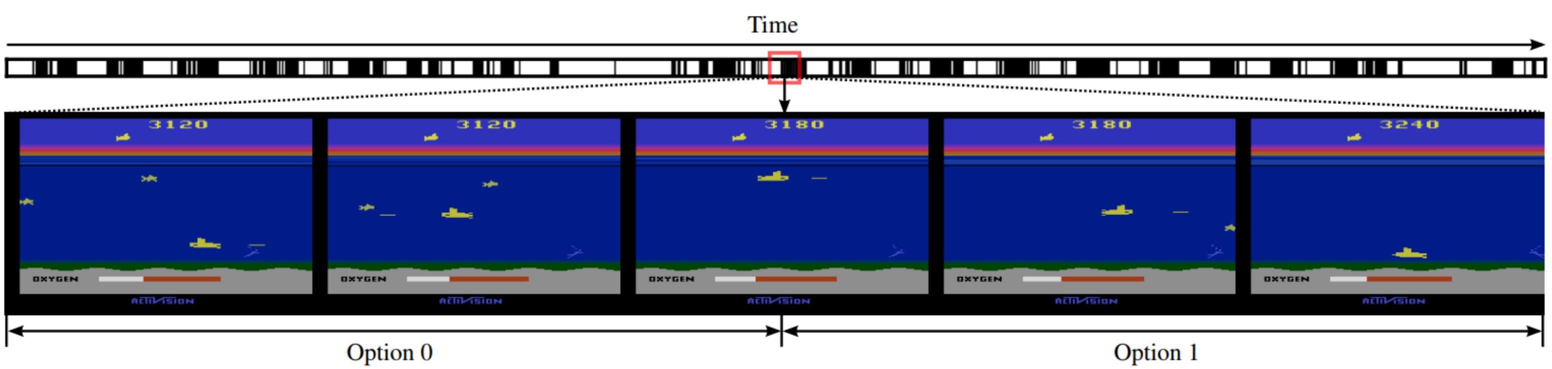
OC

- Arcade Learning Environment
  - Performance



(a) Asterix (b) Ms. Pacman (c) Seaquest (d) Zaxxon

  - Up/down specialization in the solution found by option-critic when learning with 2 options in Seaquest.



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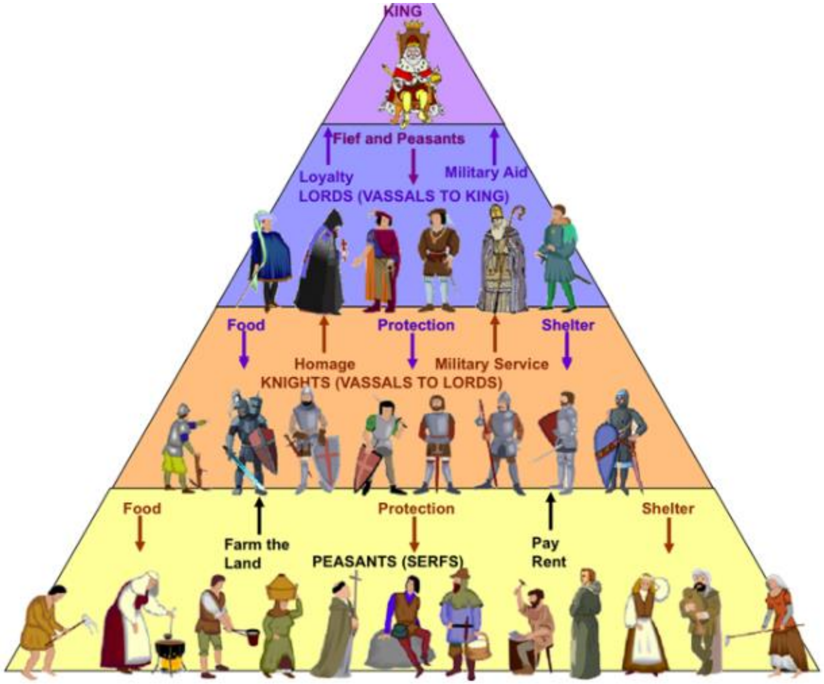
Hierarchical RL

- Discrete abstracted action
    - H-DRLN
    - OC
- Continual abstracted action
    - FuN
    - HIRO

Hierarchical RL

FuN

- Motivation
  - Goals can be generated in a top-down fashion
  - Goal setting can be decoupled from goal achievement

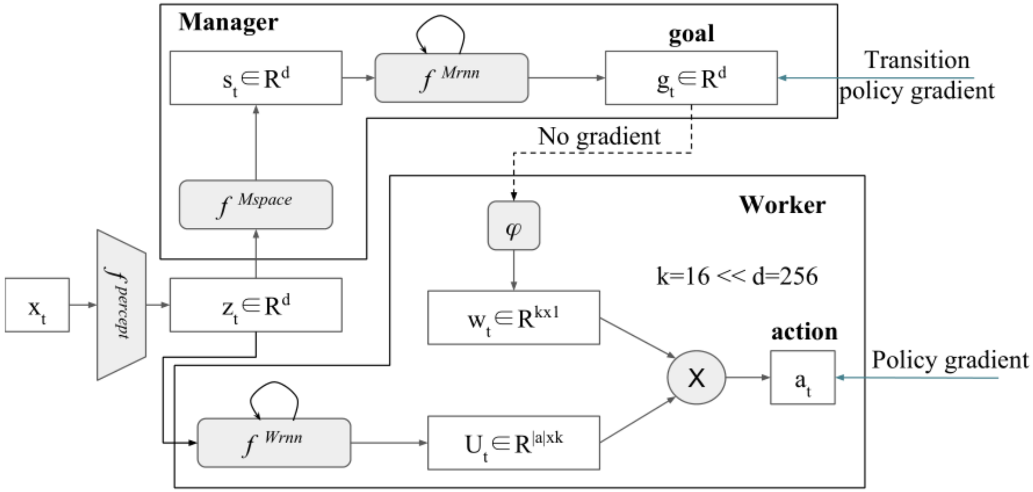


Vezhnevets, Alexander Sasha, et al. "FeUdal Networks for Hierarchical Reinforcement Learning ". *International Conference on Machine Learning* (2017).

Hierarchical RL

FuN

- The Manager and the Worker share a perceptual module
- The Manager's goals g t are trained using an approximate transition policy gradient
- The Worker is then trained via intrinsic reward to produce actions that cause these goal directions to be achieved



$$z_t = f^{\text{percept}}(x_t)$$

$$s_t = f^{Mspace}(z_t)$$

$$h_t^M, \hat{g}_t = f^{Mrnn}(s_t, h_{t-1}^M); g_t = \hat{g}_t / ||\hat{g}_t||;$$

$$w_t = \phi(\sum_{i=t-c}^{t} g_i)$$

$$h^W, U_t = f^{Wrnn}(z_t, h_{t-1}^W)$$

$$\pi_t = SoftMax(U_t w_t)$$

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Hierarchical RL

FuN

- High level:
  - The update rule:

$$\nabla g_t = A_t^M \nabla_\theta d_{\cos}(s_{t+c} - s_t, g_t(\theta)),$$

Where $A_t^M = R_t - V_t^M(x_t, \theta)$, $d_{cos}(\alpha, \beta) = \alpha^T \beta / (|\alpha||\beta|)$

- Low level:
  - Using intrinsic reward to encourage the Worker to follow the goals

$$r_t^I = 1/c \sum_{i=1}^{c} d_{\cos}(s_t - s_{t-i}, g_{t-i})$$

  - Total reward: $R_t + \alpha R_t^I$
  - The Workers policy is trained by traditional reinforcement learning algorithms.

$$\nabla \pi_t = A_t^D \nabla_\theta \log \pi(a_t | x_t; \theta)$$

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Hierarchical RL

FuN

- Transition Policy Gradients
  - The high-level policy can be composed with the transition distribution to give a 'transition policy'

$$\pi^{TP}(s_{t+c}|s_t) = p(s_{t+c}|s_t, \mu(s_t, \theta))$$

  - The policy gradient theorem can be applied to the transition policy π^{TP}, so as to find the performance gradient with respect to the policy parameters

$$\nabla_\theta \pi_t^{TP} = \mathbb{E}\left[(R_t - V(s_t))\nabla_\theta \log p(s_{t+c}|s_t, \mu(s_t, \theta))\right]$$

  - FuN assumes a particular form for the transition model: that the direction in state-space, $s_{t+c} - s_t$, follows a von Mises-Fisher distribution

$$p(s_{t+c}|s_t, o_t) \propto e^{d_{\cos}(s_{t+c}-s_t, g_t)}$$

  - If this functional form were indeed correct, then the proposed update heuristic for the Manager, is in fact the proper form for the transition policy gradient

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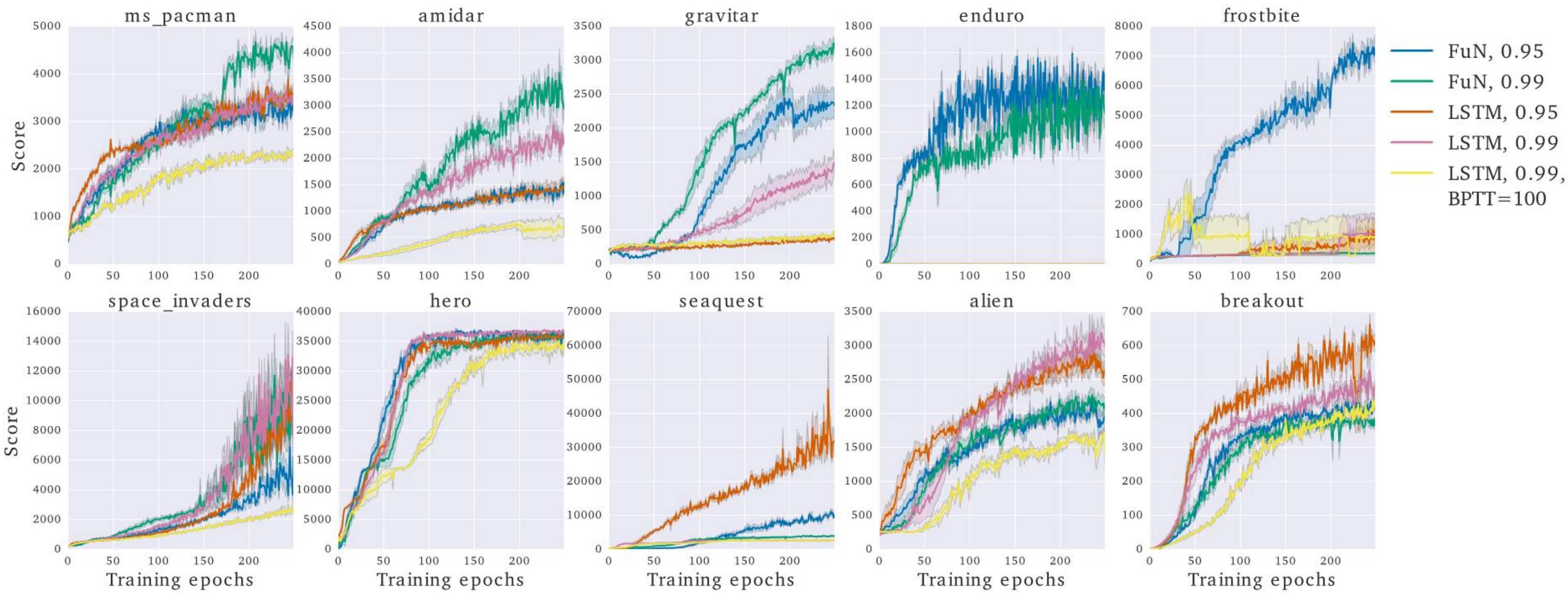
FuN

- ATARI training curves



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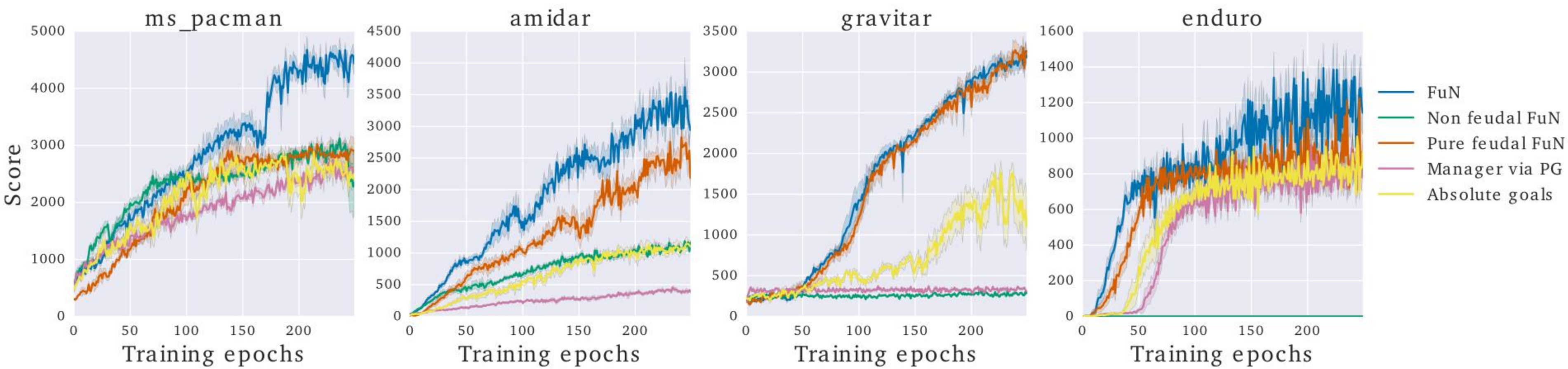
Hierarchical RL

FuN

- Ablative analysis
  - **Non feudal FuN**: the Managers output g is trained with gradients coming directly from the Worker and no intrinsic reward is used
  - **Manager via PG:** g is learnt using a standard policy gradient approach
  - **Absolute goals**: g specifies absolute, rather than relative/directional, goals
  - **Pure feudal FuN**: the Worker is trained from the intrinsic reward alone



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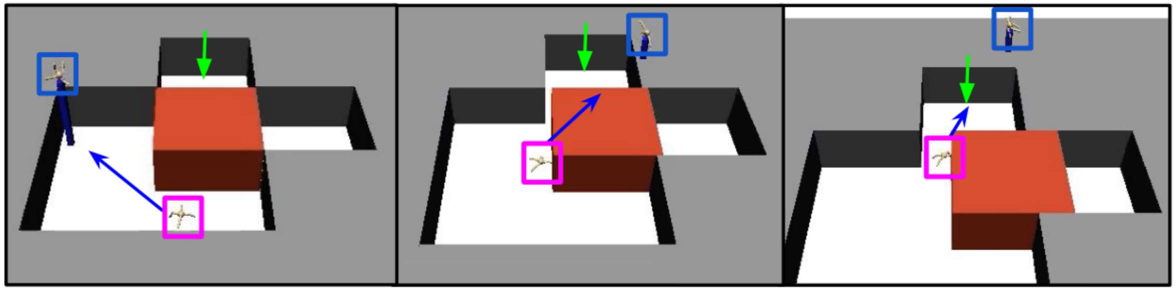
Hierarchical RL

HIRO

- Motivation
  - A successful policy must perform a complex sequence of directional movement



  - Off-policy methods are generally more efficient than off-policy methods, but also face another challenge that is unique to HRL
- Main ideas
  - Use states as goals directly, which allows for simple and fast training
  - Use off-policy training with novel off-policy correction, which is extremely sample-efficient

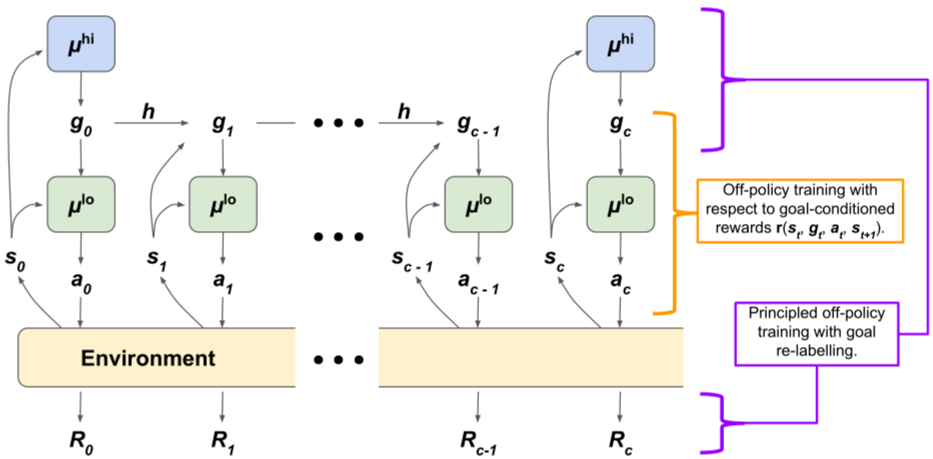
Nachum, Ofir, et al. " Data-Efficient Hierarchical Reinforcement Learning". *32nd Conference on Neural Information Processing Systems* (2018).

HIRO

- Low level
  - The rewards for training the lower-level policy is defined as:

$$r(s_t, g_t, a_t, s_{t+1}) = -||s_t + g_t - s_{t+1}||_2.$$

  - All positional observations are used as the representation for g_t, without distinguishing between the (x,y,z) root position or the joints, making for a generic and broadly applicable choice of goal space



1. Collect experience $s_t, g_t, a_t, R_t, \ldots$.
2. Train μ^{lo} with experience transitions $(s_t, g_t, a_t, r_t, s_{t+1}, g_{t+1})$ using g_t as additional state observation and reward given by goal-conditioned function $r_t = r(s_t, g_t, a_t, s_{t+1}) = -||s_t + g_t - s_{t+1}||_2$.
3. Train μ^{hi} on temporally-extended experience $(s_t, \tilde{g}_t, \sum R_{t:t+c-1}, s_{t+c})$, where $\tilde{g}_t$ is re-labelled high-level action to maximize probability of past low-level actions $a_{t:t+c-1}$.
4. Repeat.

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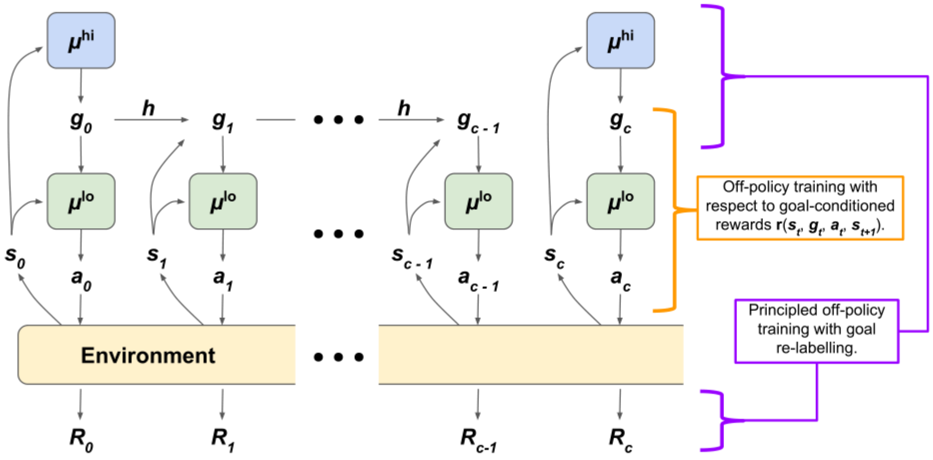
Hierarchical RL

HIRO

- High level
  - Re-labeling the high-level transition $(s_t, g_t, \sum R_{t:t+c-1}, s_{t+c})$ with a different high-level action $\tilde{g}_t$ chosen to maximize the probability $\mu^{lo}(a_{t:t+c-1}|s_{t:t+c-1}, \tilde{g}_{t:t+c-1})$
  - Most RL algorithms will use random action-space exploration to select actions, and the log probability may be computed as:

$$\log \mu^{lo}(a_{t:t+c-1}|s_{t:t+c-1}, \tilde{g}_{t:t+c-1}) \propto -\frac{1}{2}\sum_{i=t}^{t+c-1} ||a_i - \mu^{lo}(s_i, \tilde{g}_i)||_2^2 + \text{const.}$$



1. Collect experience $s_t, g_t, a_t, R_t, \ldots$.
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4. Repeat.

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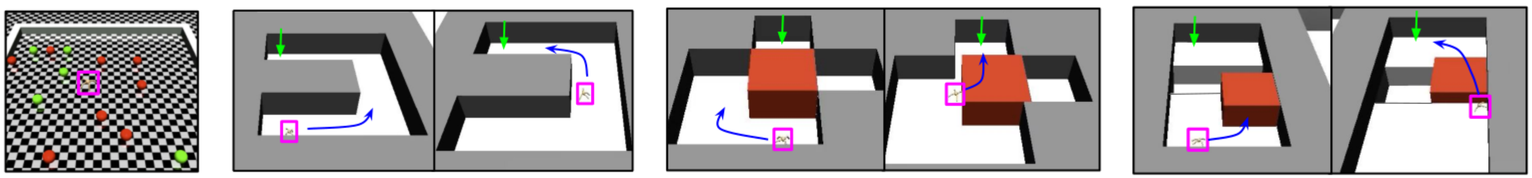
Hierarchical RL

HIRO

- Experiments
  - Scene screenshot



  - performance

	Ant Gather	Ant Maze	Ant Push	Ant Fall
HIRO	**3.02±1.49**	**0.99±0.01**	**0.92±0.04**	**0.66±0.07**
FuN representation	0.03 ± 0.01	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0
FuN transition PG	0.41 ± 0.06	0.0 ± 0.0	0.56 ± 0.39	0.01 ± 0.02
FuN cos similarity	0.85 ± 1.17	0.16 ± 0.33	0.06 ± 0.17	0.07 ± 0.22
FuN	0.01 ± 0.01	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0
SNN4HRL	1.92 ± 0.52	0.0 ± 0.0	0.02 ± 0.01	0.0 ± 0.0
VIME	1.42 ± 0.90	0.0 ± 0.0	0.02 ± 0.02	0.0 ± 0.0

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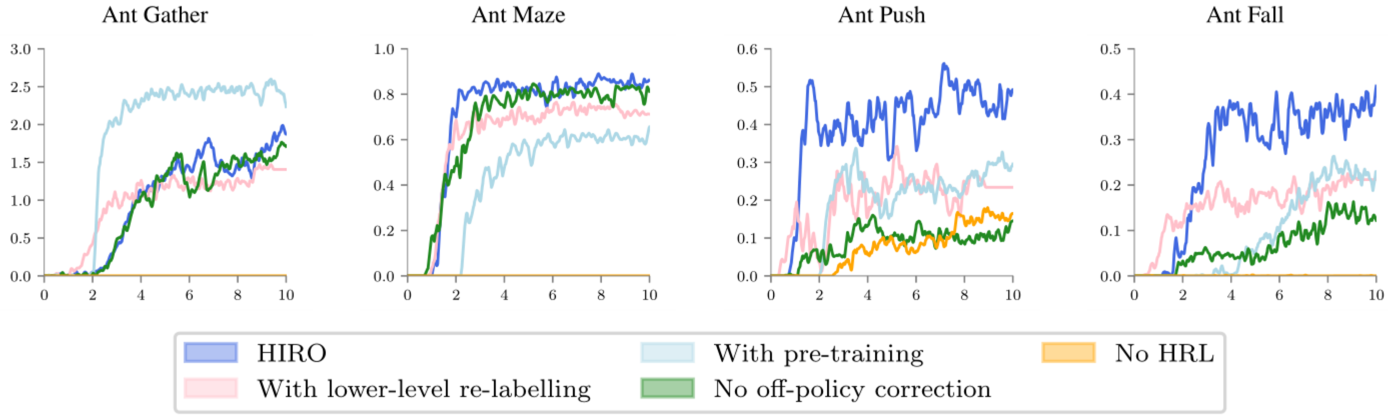
Hierarchical RL

HIRO

- Ablative Analysis
  - **With lower-level re-labelling**: increase the amount of data available to an agent trained using a parameterized reward (the lower-level policy in our setup) by re-labeling experiences with randomly sampled goals.
  - **With pre-training**: pre-train the lower-level policy for 2M steps (using goals sampled from a Gaussian) before freezing it and training the higher-level policy alone
  - **No off-policy correction**
  - **No HRL**



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