Hierarchical RL and Skill Discovery

CS 330

The Plan

Information-theoretic concepts

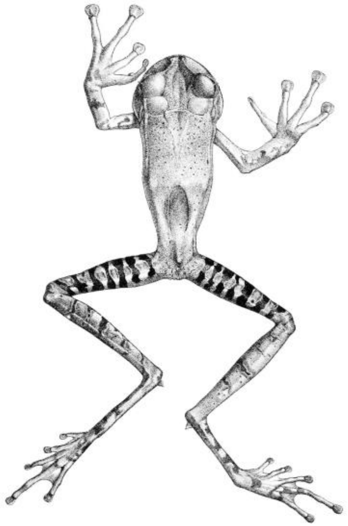
Skill discovery

Using discovered skills

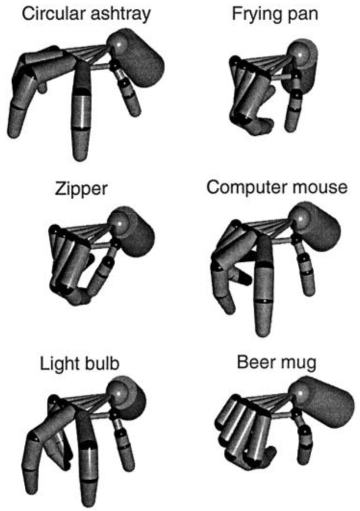
Hierarchical RL

Why Skill Discovery?

What if we want to discover interesting behaviors?



[The construction of movement by the spinal cord, *Tresch et al.*, 1999]

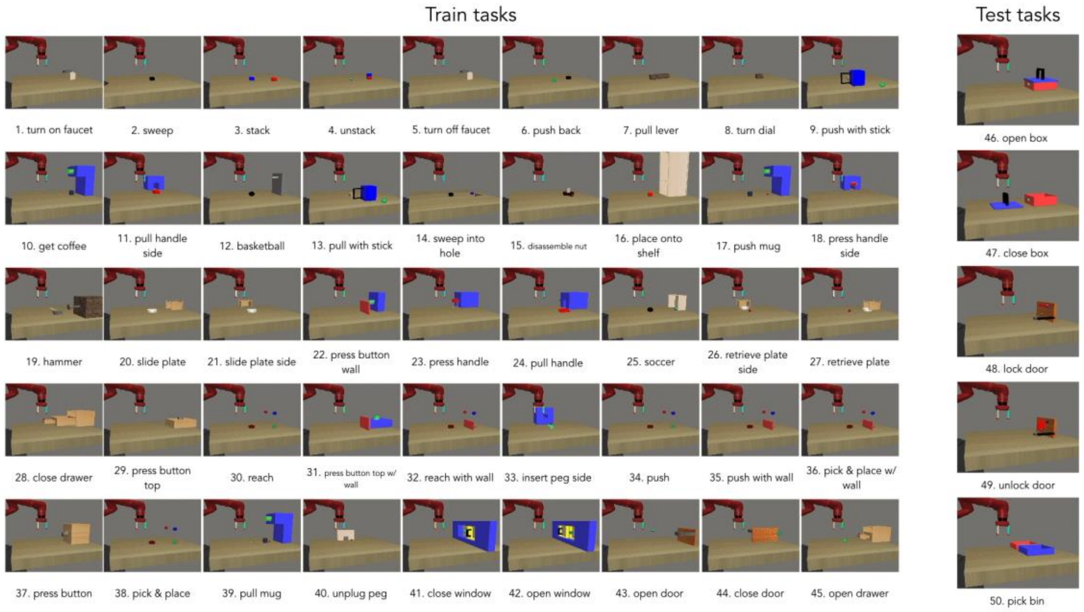


[Postural hand synergies for tool use, *Santello, et al.*, 1998]

Why Skill Discovery? More practical version

Coming up with tasks is tricky…

Write down task ideas for a tabletop manipulation scenario



[Meta-World, *Yu, Quillen, He, et al.*, 2019]

Why Hierarchical RL?

Performing tasks at various levels of abstractions

Bake a cheesecake

Buy ingredients

Go to the store

Walk to the door

Take a step

Contract muscle X

Exploration

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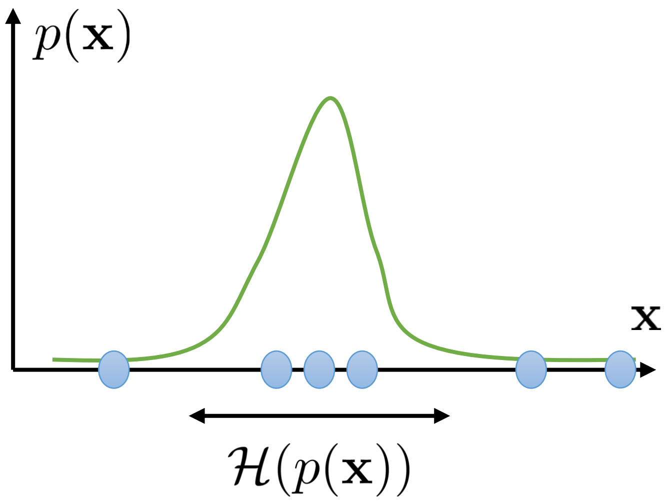
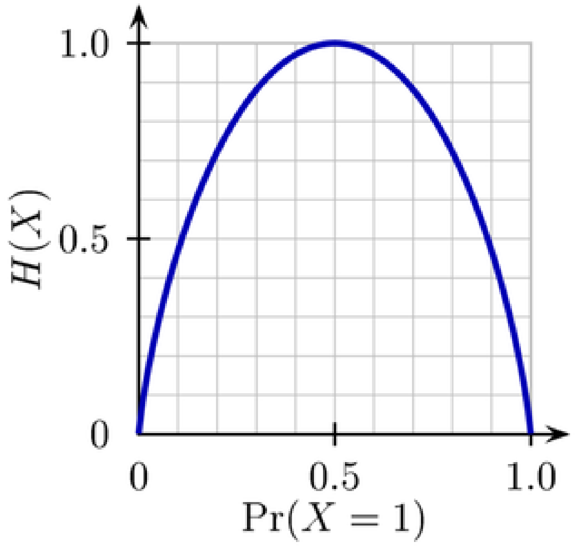
Entropy

$p(\mathbf{x})$ distribution (e.g., over observations $\mathbf{x}$)

$$\mathcal{H}(p(\mathbf{x})) = -E_{\mathbf{x}\sim p(\mathbf{x})}[\log p(\mathbf{x})]$$

entropy – how "broad" $p(\mathbf{x})$ is

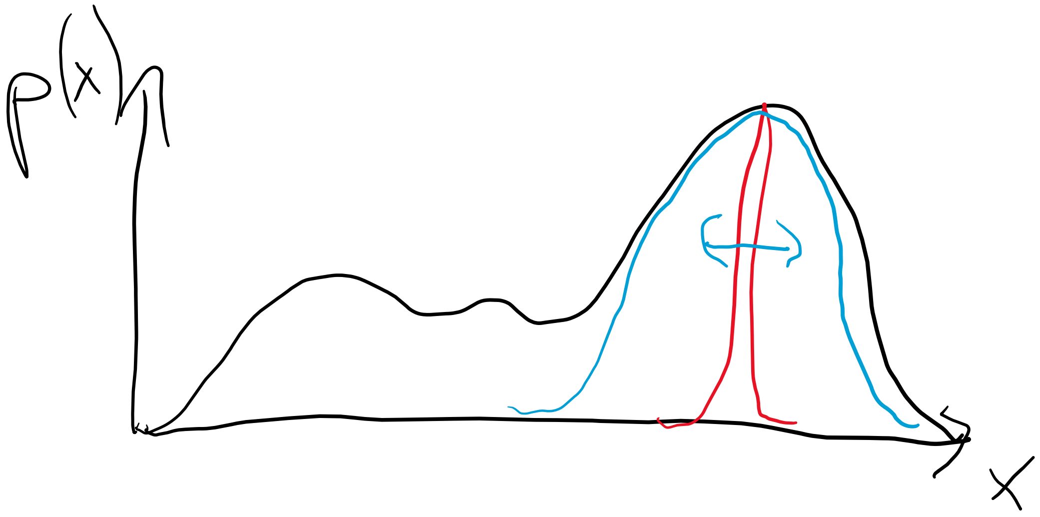




KL-divergence

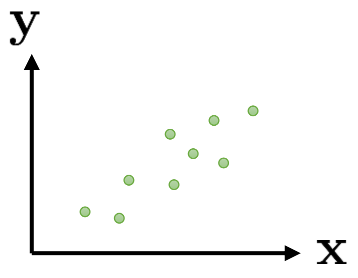
Distance between two distributions

$$\mathbb{D}_{KL}(q||p) = \mathbb{E}_q\Big[\log\frac{q(x)}{p(x)}\Big] = \mathbb{E}_q \log q(x) - \mathbb{E}_q \log p(x) = \underline{-\mathbb{E}_q \log p(x)} - \underline{\mathcal{H}(q(x))}$$

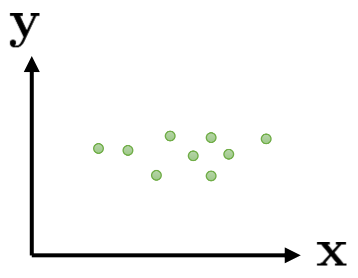


Mutual information

$$\mathcal{I}(\mathbf{x};\mathbf{y}) = D_{\mathrm{KL}}(p(\mathbf{x},\mathbf{y})\|p(\mathbf{x})p(\mathbf{y}))$$
$$= E_{(\mathbf{x},\mathbf{y})\sim p(\mathbf{x},\mathbf{y})}\left[\log \frac{p(\mathbf{x},\mathbf{y})}{p(\mathbf{x})p(\mathbf{y})}\right]$$
$$= \mathcal{H}(p(\mathbf{y})) - \mathcal{H}(p(\mathbf{y}|\mathbf{x})) = \mathcal{H}(p(\mathbf{x})) - \mathcal{H}(p(\mathbf{x}|\mathbf{y}))$$



high MI: $\mathbf{x}$ and $\mathbf{y}$ are *dependent*



low MI: $\mathbf{x}$ and $\mathbf{y}$ are *independent*

High MI?

x- it rains tomorrow, y – streets are wet tomorrow

x- it rains tomorrow, y – we find life on Mars tomorrow

Slide adapted from Sergey Levine

Mutual information

$$\mathcal{I}(\mathbf{x};\mathbf{y}) = D_{\mathrm{KL}}(p(\mathbf{x},\mathbf{y})\|p(\mathbf{x})p(\mathbf{y}))$$
$$= E_{(\mathbf{x},\mathbf{y})\sim p(\mathbf{x},\mathbf{y})}\left[\log \frac{p(\mathbf{x},\mathbf{y})}{p(\mathbf{x})p(\mathbf{y})}\right]$$
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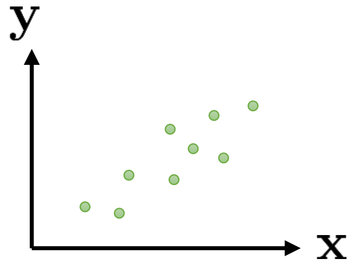
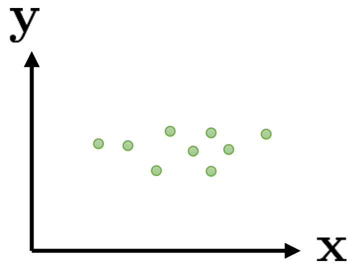


high MI: $\mathbf{x}$ and $\mathbf{y}$ are *dependent*



low MI: $\mathbf{x}$ and $\mathbf{y}$ are *independent*

example of mutual information: "empowerment" (Polani et al.)

$$\mathcal{I}(\mathbf{s}_{t+1};\mathbf{a}_t) = \mathcal{H}(\mathbf{s}_{t+1}) - \mathcal{H}(\mathbf{s}_{t+1}|\mathbf{a}_t)$$

Slide adapted from Sergey Levine

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Soft Q-learning

Objective:

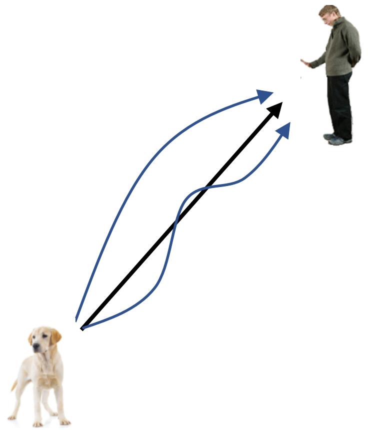
$$\sum_t E_{(\mathbf{s}_t,\mathbf{a}_t)\sim q}\left[r(\mathbf{s}_t,\mathbf{a}_t) + \mathcal{H}(q(\mathbf{a}_t|\mathbf{s}_t))\right]$$

Value-, Q-functions, and the policy

$$V_t(\mathbf{s}_t) = \log \int \exp(Q_t(\mathbf{s}_t,\mathbf{a}_t))\mathbf{a}_t$$

$$Q_t(\mathbf{s}_t,\mathbf{a}_t) = r(\mathbf{s}_t,\mathbf{a}_t) + E[(V_{t+1}(\mathbf{s}_{t+1})]$$

$$\pi(\mathbf{a}_t|\mathbf{s}_t) = \exp(Q_t(\mathbf{s}_t,\mathbf{a}_t) - V_t(\mathbf{s}_t)) = \exp(A_t(\mathbf{s}_t,\mathbf{a}_t))$$



Q-learning

1. collect dataset $\{(\mathbf{s}_i,\mathbf{a}_i,\mathbf{s}'_i,r_i)\}$
2. set $\mathbf{y}_i \leftarrow r(\mathbf{s}_i,\mathbf{a}_i) + \gamma \max_{\mathbf{a}'_i} Q_\phi(\mathbf{s}'_i,\mathbf{a}'_i)$
3. set $\phi \leftarrow \arg\min_\phi \frac{1}{2}\sum_i \|Q_\phi(\mathbf{s}_i,\mathbf{a}_i) - \mathbf{y}_i\|^2$

$K\times$

$$\pi(\mathbf{a}|\mathbf{s}) = \arg\max_{\mathbf{a}} Q_\phi(\mathbf{s},\mathbf{a})$$

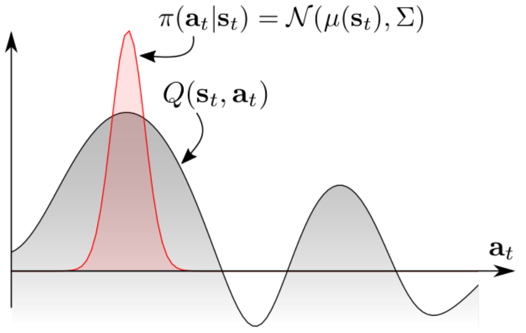
Soft Q-learning

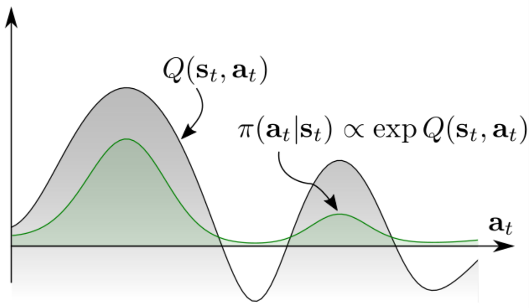
1. collect dataset $\{(\mathbf{s}_i,\mathbf{a}_i,\mathbf{s}'_i,r_i)\}$
2. set $\mathbf{y}_i \leftarrow r(\mathbf{s}_i,\mathbf{a}_i) + \gamma \cancel{\max}_{\mathbf{a}'_i} Q_\phi(\mathbf{s}'_i,\mathbf{a}'_i)$ softmax
3. set $\phi \leftarrow \arg\min_\phi \frac{1}{2}\sum_i \|Q_\phi(\mathbf{s}_i,\mathbf{a}_i) - \mathbf{y}_i\|^2$

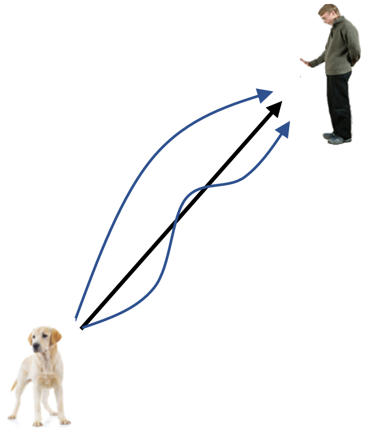
$K\times$

$$\pi(\mathbf{a}|\mathbf{s}) = \cancel{\arg\max_{\mathbf{a}} Q_\phi(\mathbf{s},\mathbf{a})} \quad \exp(A_t(s_t, a_t))$$

Soft Q-learning



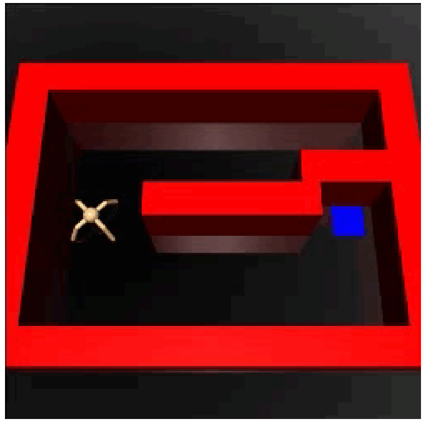


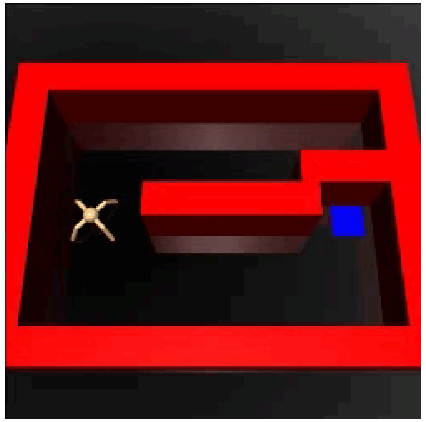


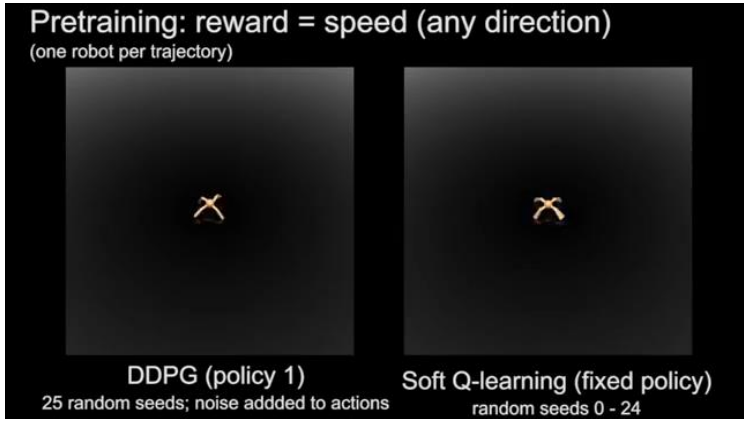
Exploration

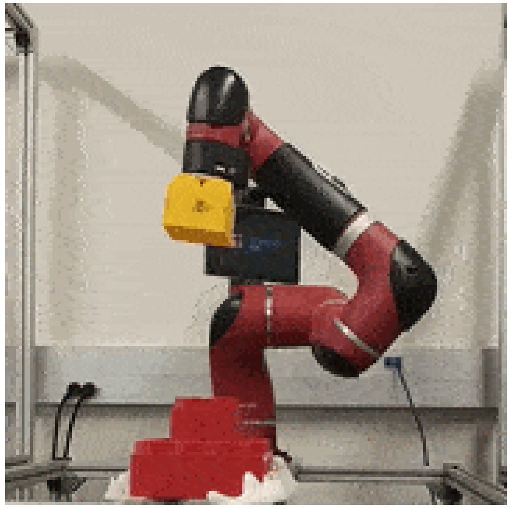
Fine-tunability

Robustness









 Haarnoja et al. RL with Deep Energy-Based Policies, 2017

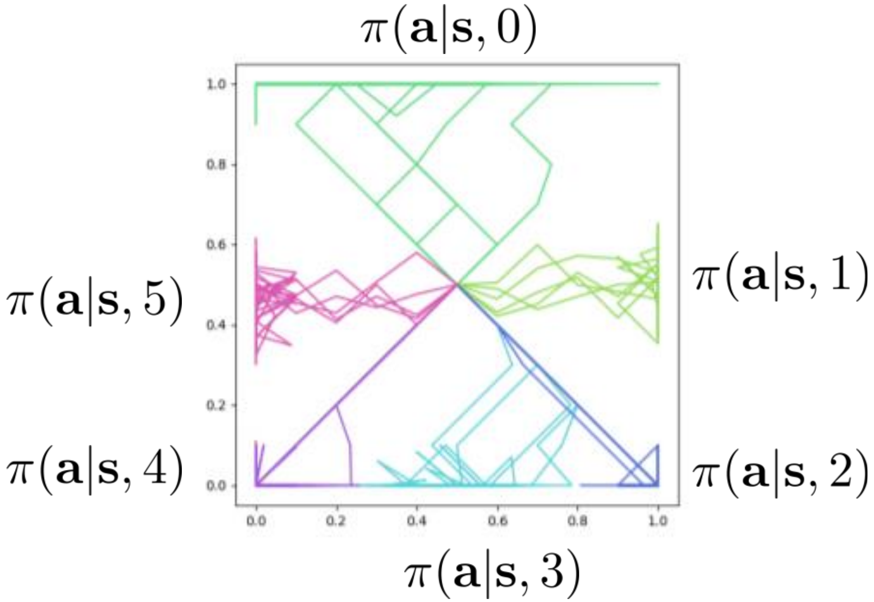
Learning diverse skills

$$\pi(\mathbf{a}|\mathbf{s}, z)$$

task index

Why can't we just use MaxEnt RL

1. **action** entropy is not the same as **state** entropy
   agent can take very different actions, but land in similar states
2. MaxEnt policies are stochastic, but not always **controllable**
   intuitively, we want **low** diversity for a fixed z, high diversity *across* z's



Intuition: different **skills** should visit different **state-space regions**

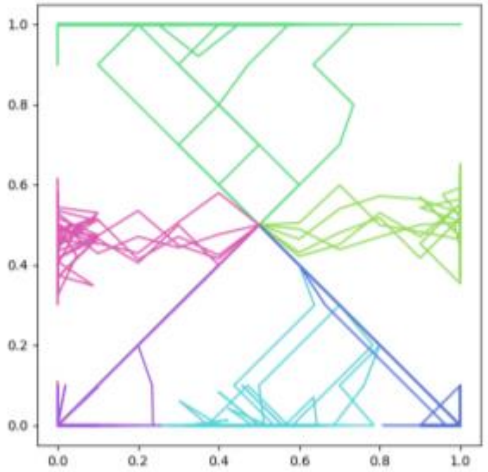
Eysenbach, Gupta, Ibarz, Levine. **Diversity is All You Need.**

Slide adapted from Sergey Levine

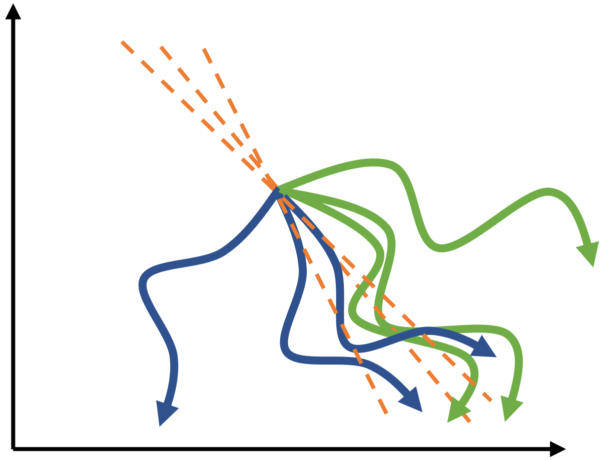
Diversity-promoting reward function

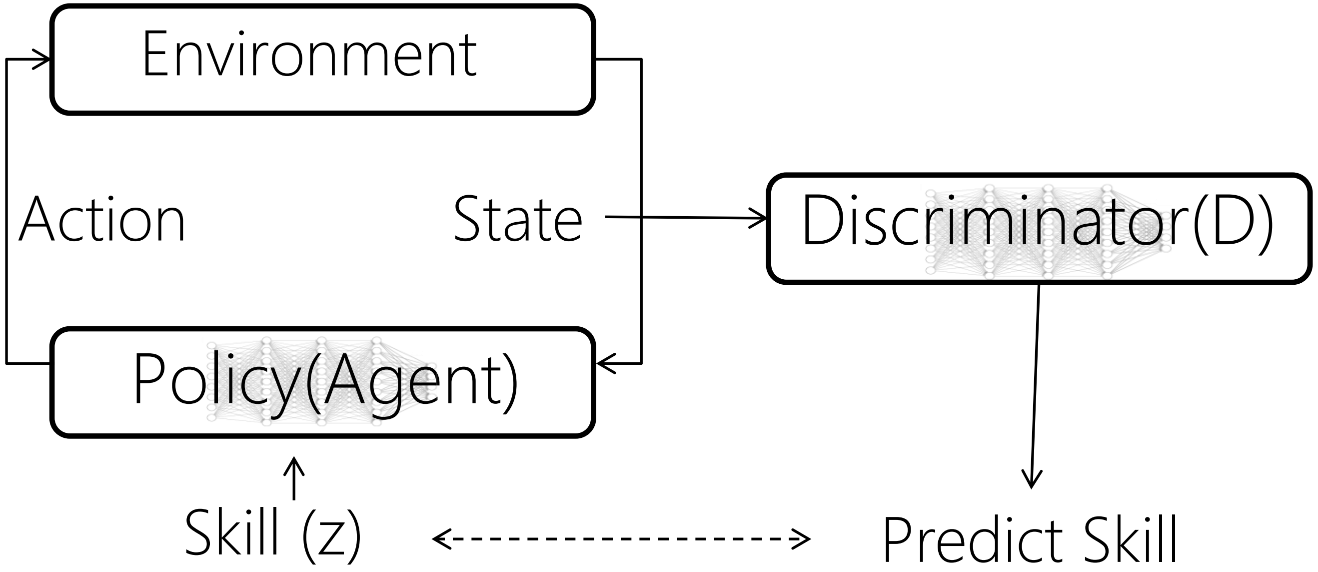
$$\pi(\mathbf{a}|\mathbf{s}, z) = \arg\max_{\pi} \sum_{z} E_{\mathbf{s}\sim\pi(\mathbf{s}|z)}[r(\mathbf{s}, z)]$$

reward states that are unlikely for other $z' \neq z$



$$r(\mathbf{s}, z) = \log p(z|\mathbf{s})$$

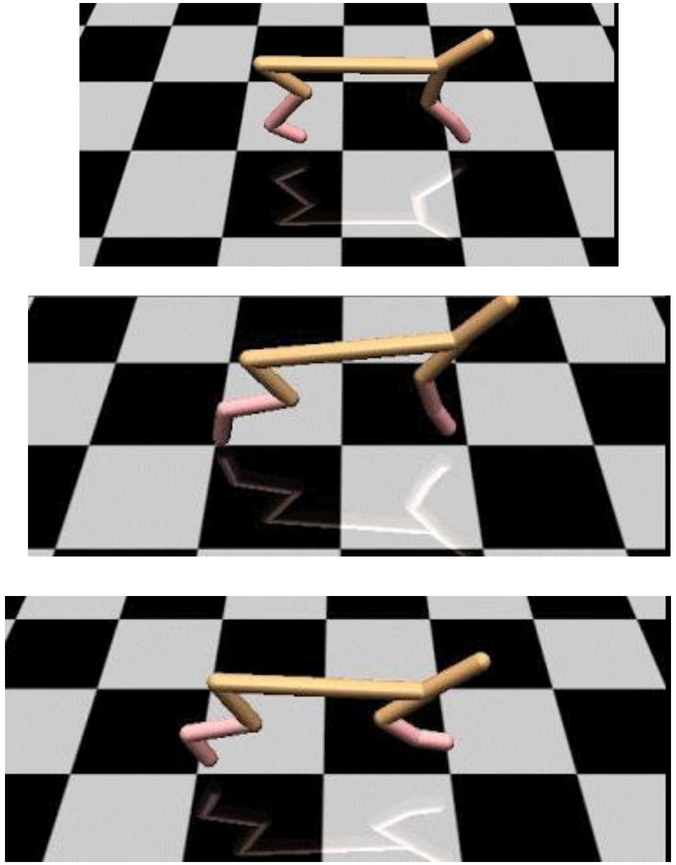




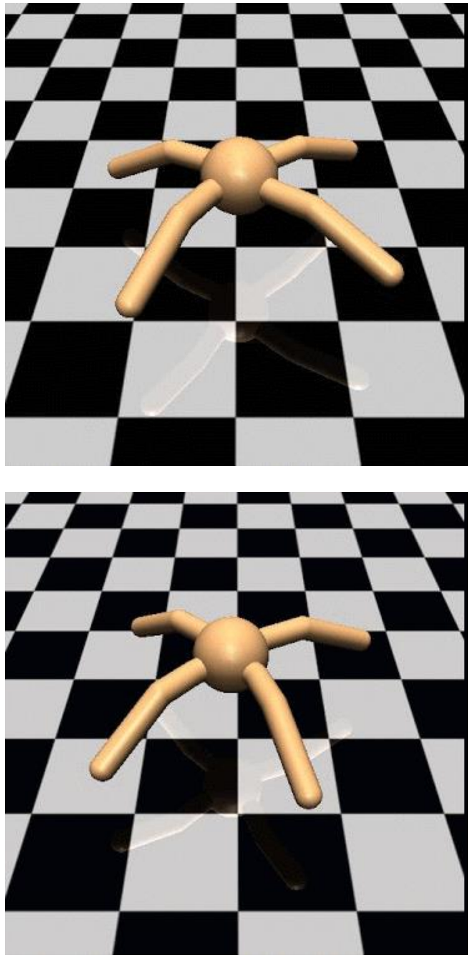
Eysenbach, Gupta, Ibarz, Levine. Diversity is All You Need.

Slide adapted from Sergey Levine

Examples of learned tasks



Cheetah



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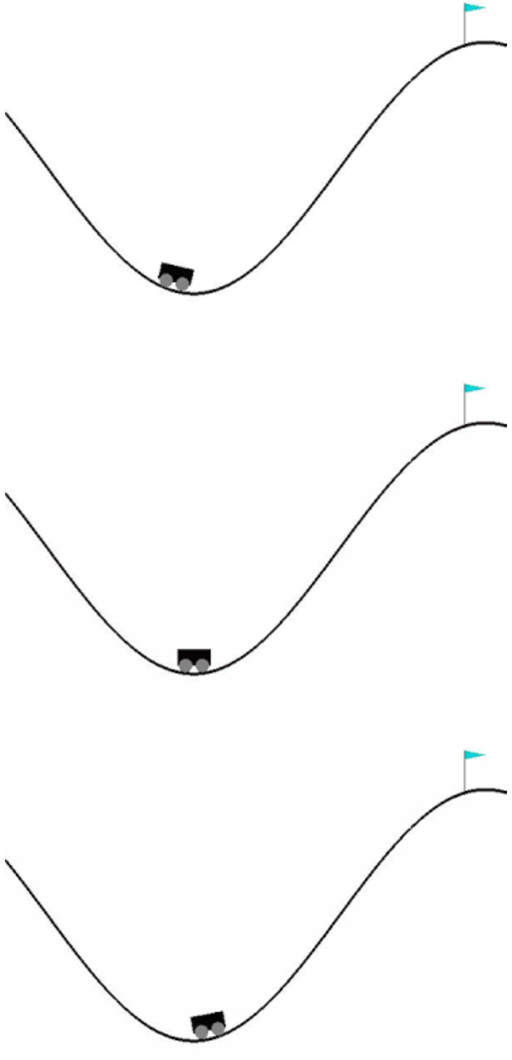

Mountain car

Eysenbach, Gupta, Ibarz, Levine. **Diversity is All You Need.**

A connection to mutual information

$$\pi(\mathbf{a}|\mathbf{s}, z) = \arg\max_{\pi} \sum_{z} E_{\mathbf{s}\sim\pi(\mathbf{s}|z)}[r(\mathbf{s}, z)]$$

$$r(\mathbf{s}, z) = \log p(z|\mathbf{s})$$

$$I(z, \mathbf{s}) = H(z) - H(z|s)$$

maximized by using uniform prior $p(z)$

minimized by maximizing $\log p(z|\mathbf{s})$

Eysenbach, Gupta, Ibarz, Levine. Diversity is All You Need.

See also: Gregor et al. Variational Intrinsic Control. 2016

Slide adapted from Sergey Levine

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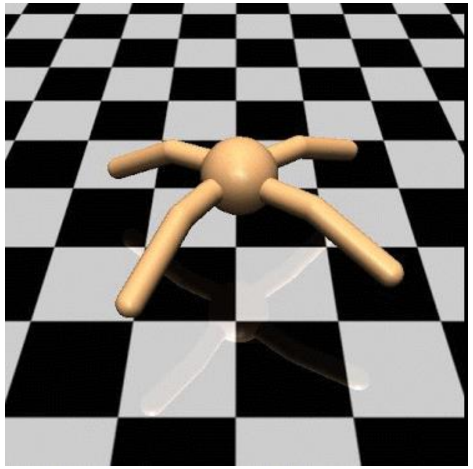
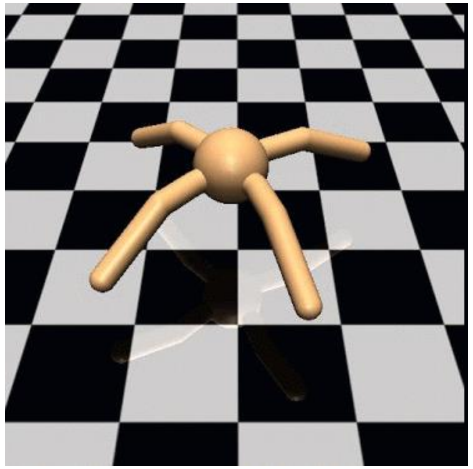
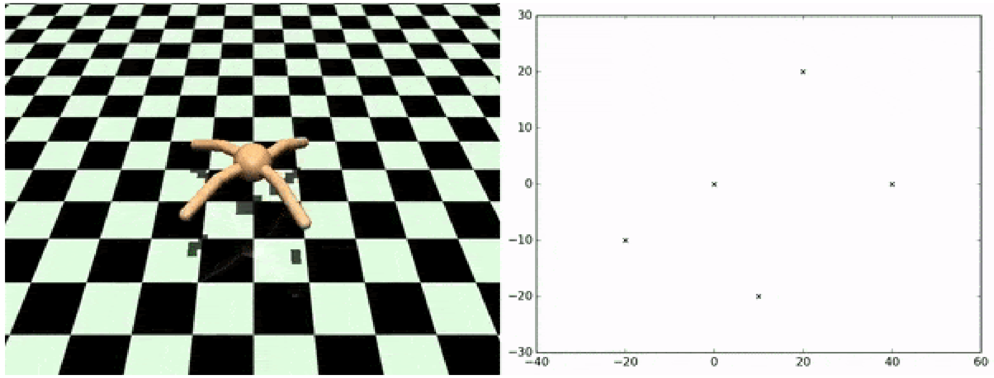
How to use learned skills?

$$\pi(\mathbf{a}|\mathbf{s}, z)$$





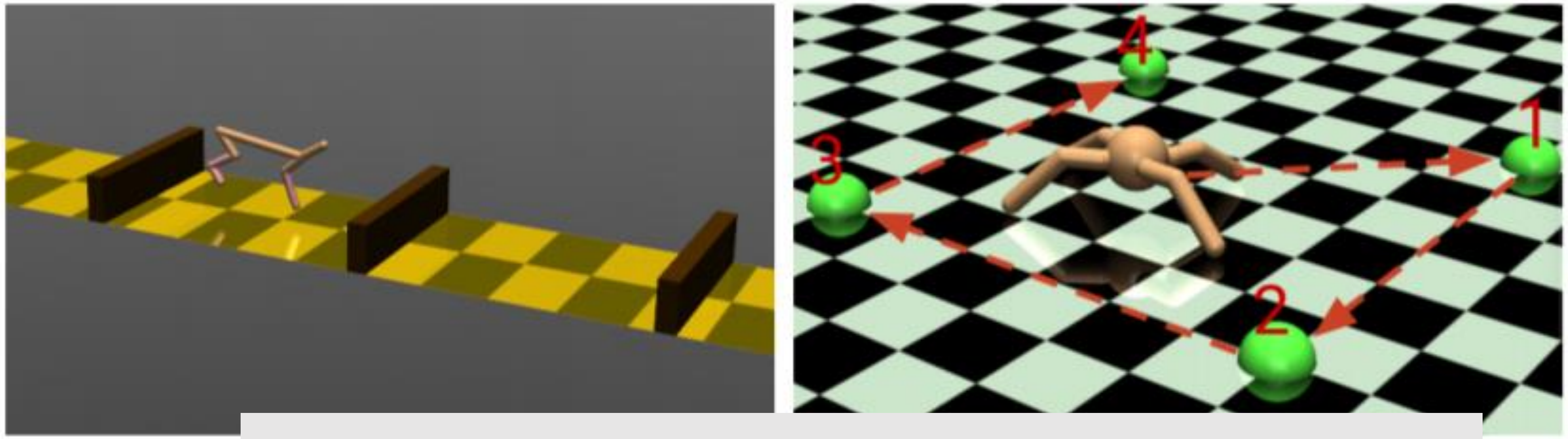
How can we use the learned skills to accomplish a task?



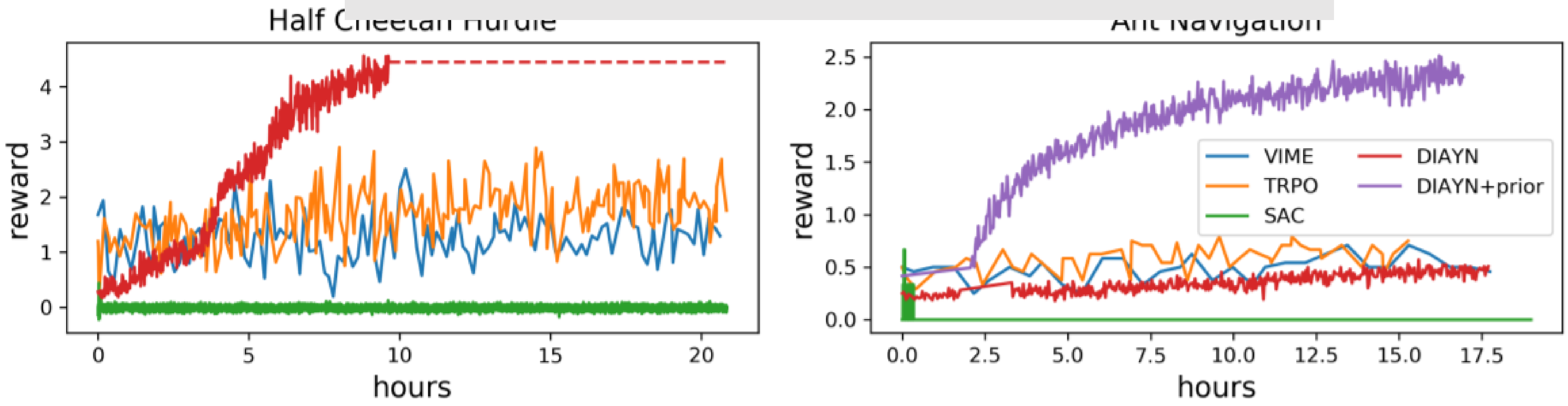
Learn a policy that operates on z's

Eysenbach, Gupta, Ibarz, Levine. Diversity is All You Need.

Results: hierarchical RL



Can we do better?

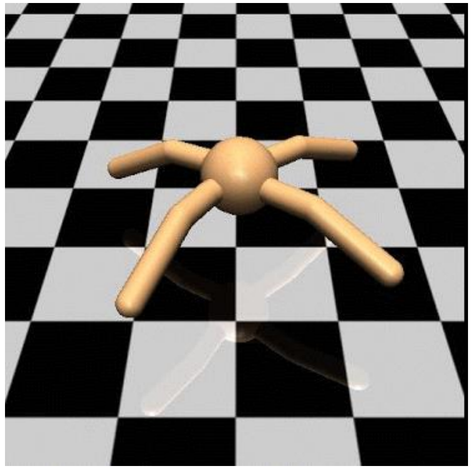


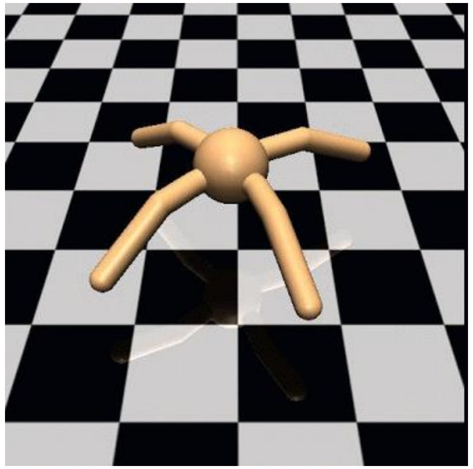
Eysenbach, Gupta, Ibarz, Levine. **Diversity is All You Need.**

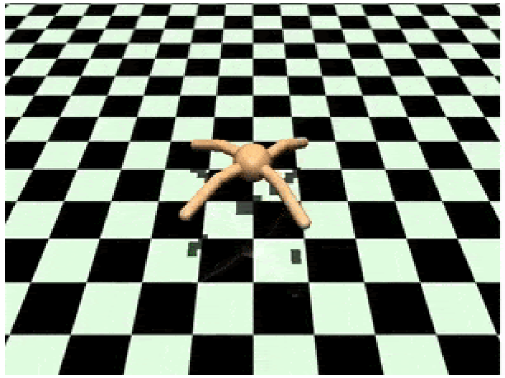
What’s the problem?

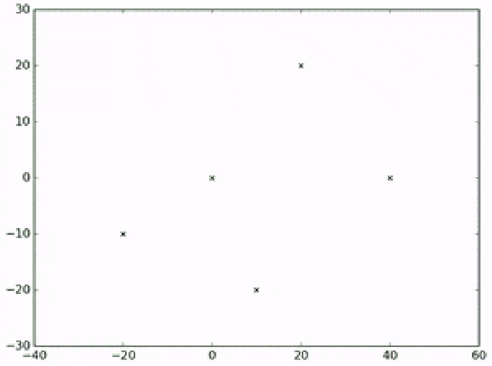
Skills might not be particularly useful

It’s not very easy to use the learned skills





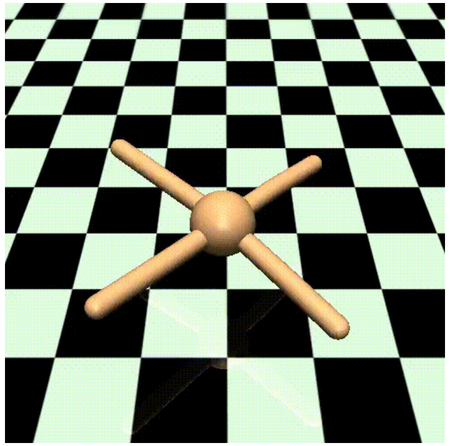


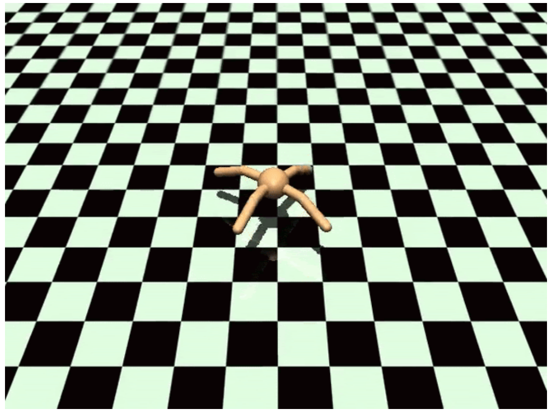


What makes a useful skill?

What’s the problem?

Consequences are **hard** to predict





Consequences are **easy** to predict

Slightly different mutual information

$$I(z, \mathbf{s}) = H(z) - H(z|s)$$

$$\max \mathcal{I}(s', z \mid s) = \max \left(\mathcal{H}(s' \mid s) - \mathcal{H}(s' \mid s, z) \right)$$

$I(x, y | z)$ $p(x, y | z)$ $p(x | z)$ $p(y | z)$

$$\mathcal{I}(\mathbf{x}; \mathbf{y}) = D_{\mathrm{KL}}(p(\mathbf{x}, \mathbf{y}) \| p(\mathbf{x}) p(\mathbf{y}))$$

Future hard to predict for different skills

Predictable future for a given skill

$$I(s'; z|s) \geq \mathbb{E}_s \mathbb{E}_z \mathbb{E}_{p(s'|s,z)} [\log \frac{q_\phi(s'|s, z)}{p(s'|s)}]$$

$$\approx \mathbb{E}_s \mathbb{E}_z \mathbb{E}_{p(s'|s,z)} [\log \frac{q_\phi(s'|s, z)}{\sum_{i=1}^{L} q_\phi(s'|s, z_i)} + \log L]$$

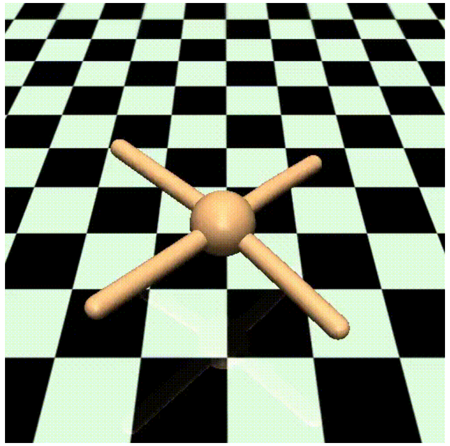
Sharma, Gu, Levine, Kumar, Hausman, DADS, 2019.

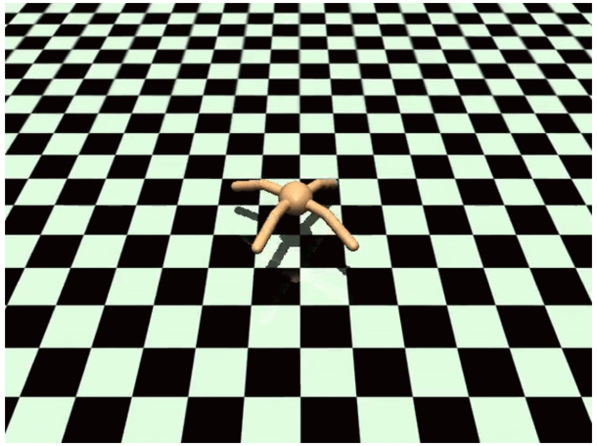
Skill-dynamics model

We are learning a skill-dynamics model $q(s' \mid s, z)$

compared to conventional global dynamics $p(s' \mid s, a)$

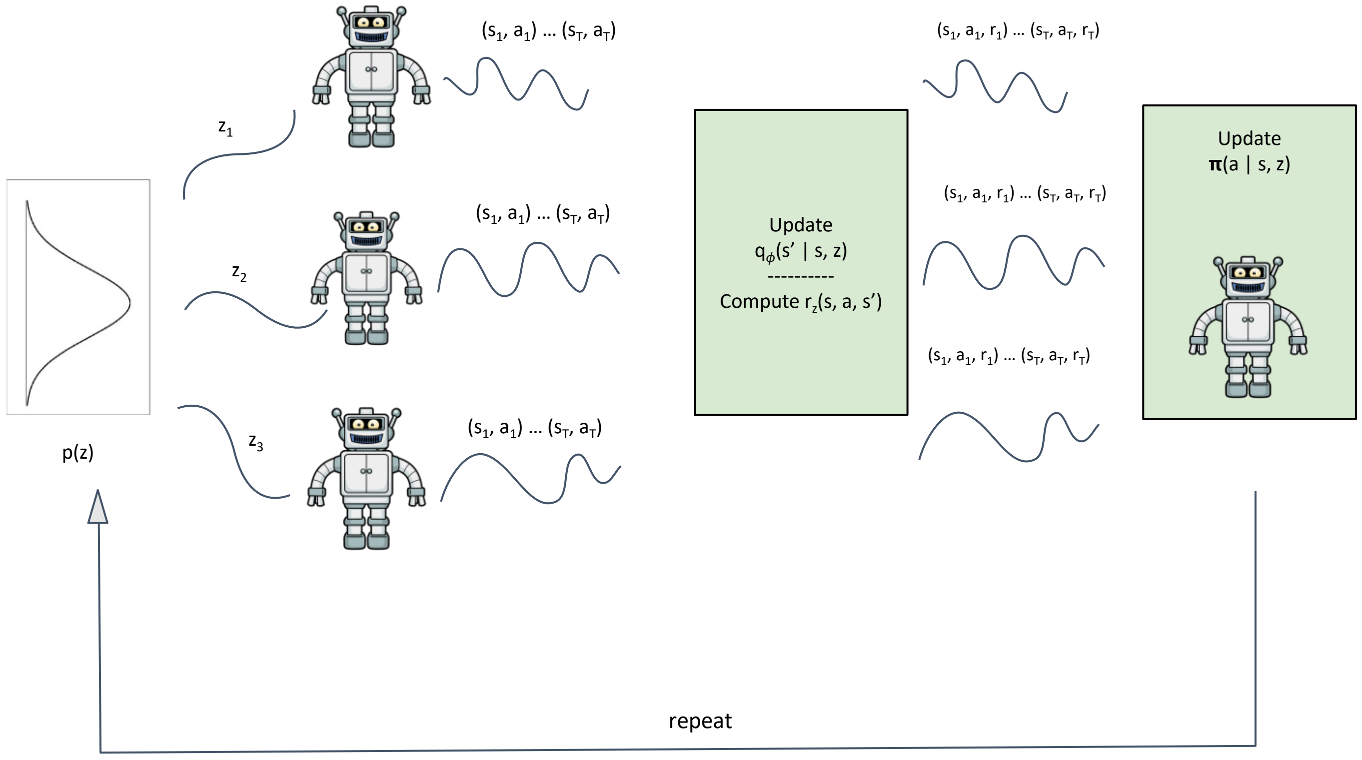
Skills are optimized specifically to make skill-dynamics easier to model





Sharma, Gu, Levine, Kumar, Hausman, DADS, 2019.

DADS algorithm

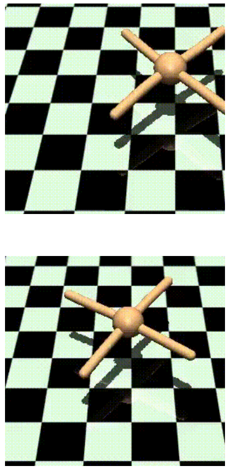


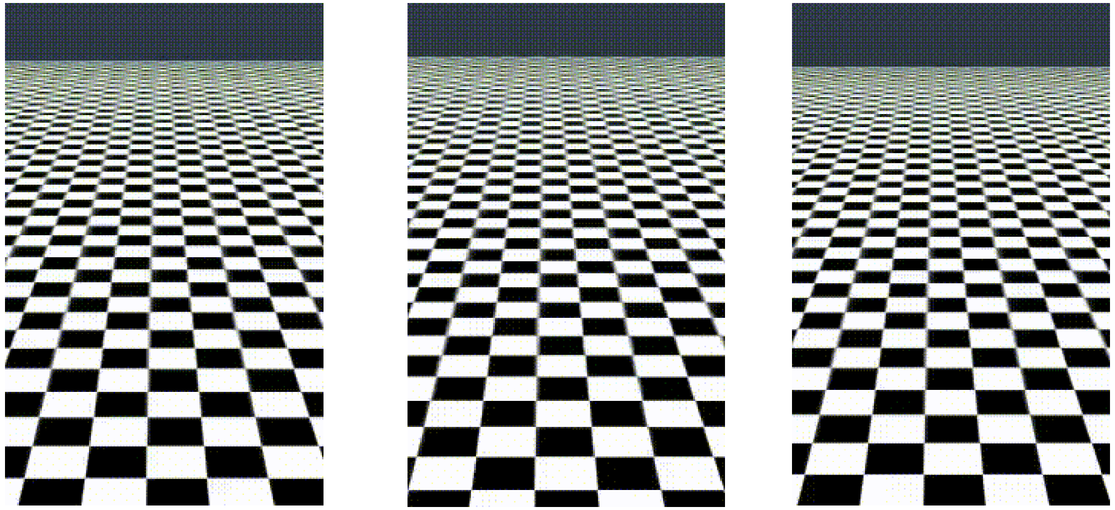
Algorithm 1: Dynamics-Aware Discovery of Skills (DADS)

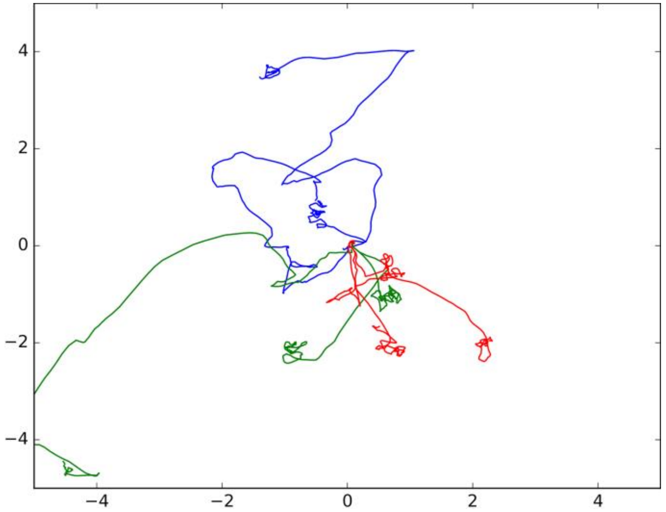
Initialize π, q_ϕ;
while *not converged* **do**
  Sample a skill $z \sim p(z)$ every episode;
  Collect new M on-policy samples;
  Update q_ϕ using K_1 steps of gradient descent on M transitions;
  Compute $r_z(s, a, s')$ for M transitions;
  Update π using any RL algorithm;
end

Sharma, Gu, Levine, Kumar, Hausman, DADS, 2019.

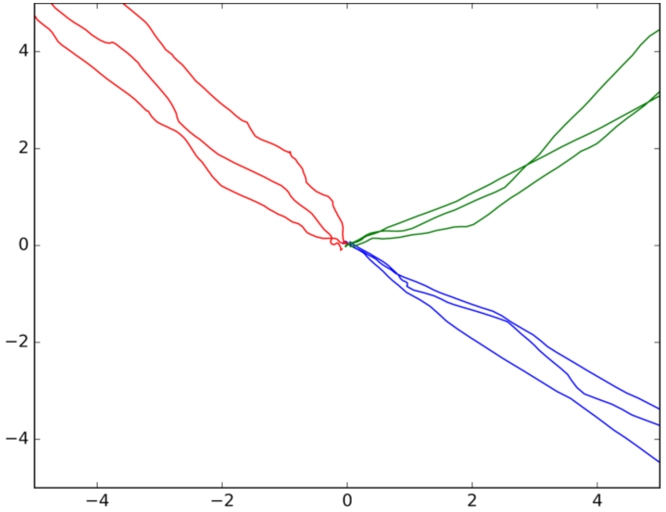
DADS results





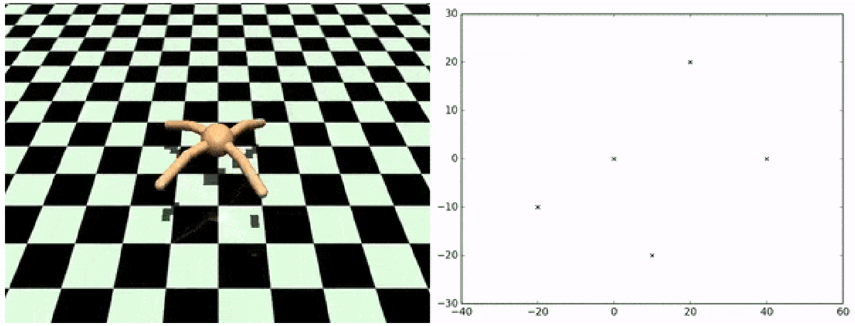


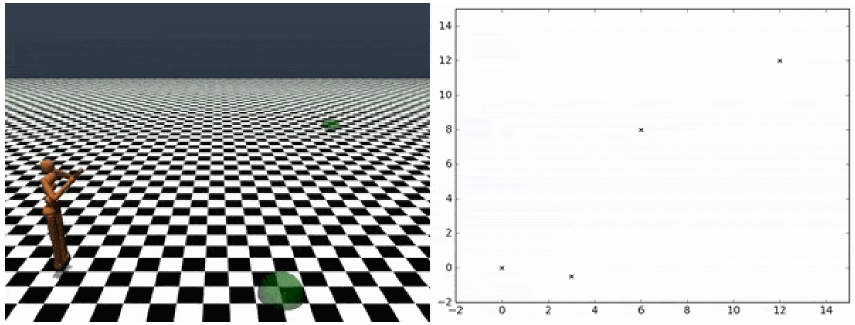
DIAYN



DADS

Using learned skills

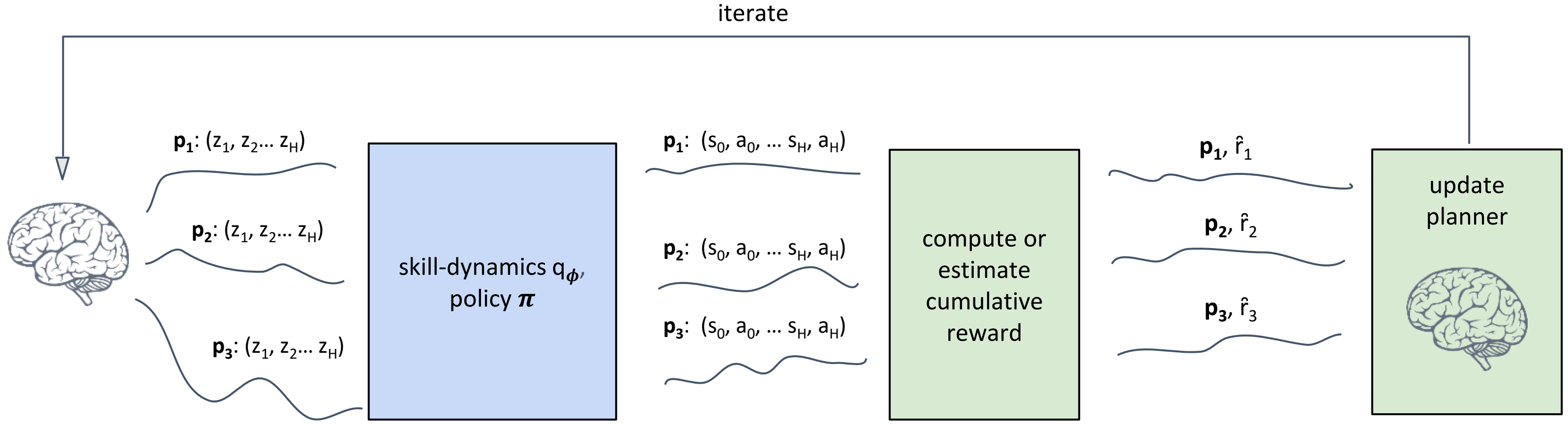




Use skill-dynamics for model-based planning

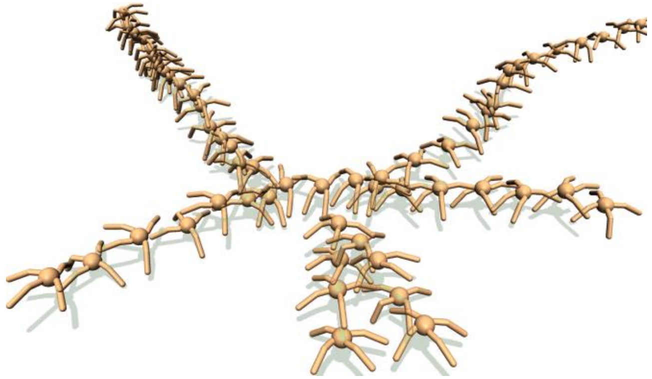
Plan for skills not actions

Tasks can be learned zero-shot



Summary

- Two skill discovery algorithms that use mutual information
- Predictability can be used as a proxy for “usefulness”
- Method that optimizes for both, predictability and diversity
- Model-based planning in the skill space
- Opens new avenues such as unsupervised meta-RL
    - Gupta et al. *Unsupervised Meta-Learning for RL*, 2018



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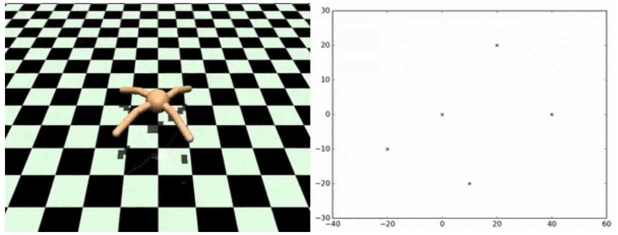
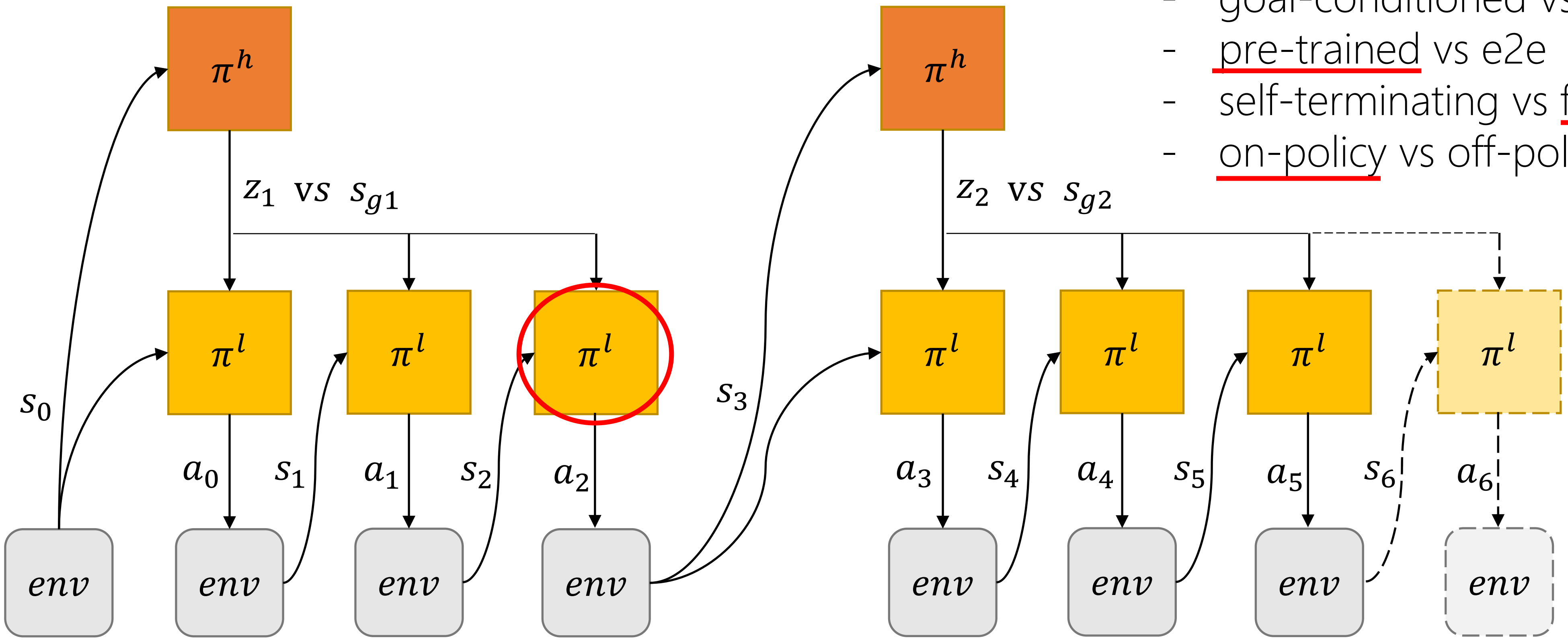
Exploration

Hierarchical RL – design choices



Design choices:

- goal-conditioned vs not
- pre-trained vs e2e
- self-terminating vs fixed rate
- on-policy vs off-policy



Learning Locomotor Controllers

Command updated
every K steps

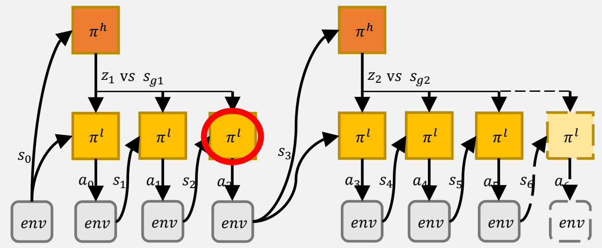
High-level
controller

[redacted]

w-level
ntroller

inform

- HL and LL trained separately
- Trained with policy gradients
- Hierarchical noise



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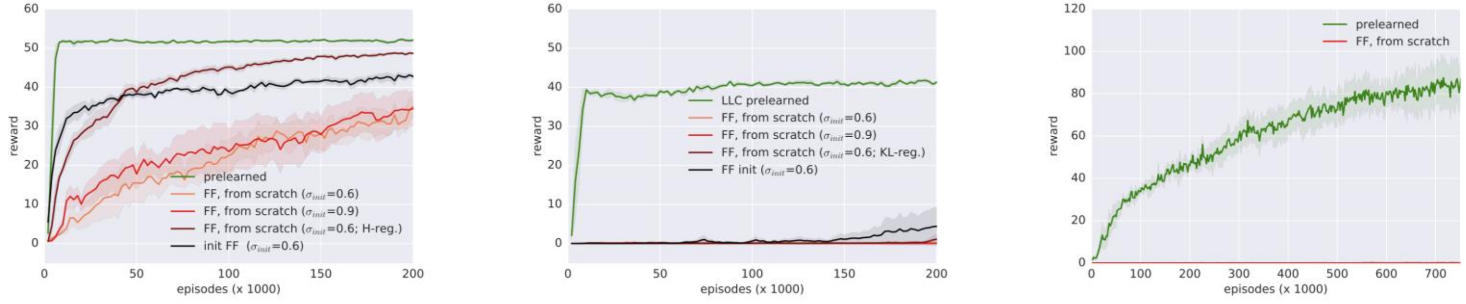
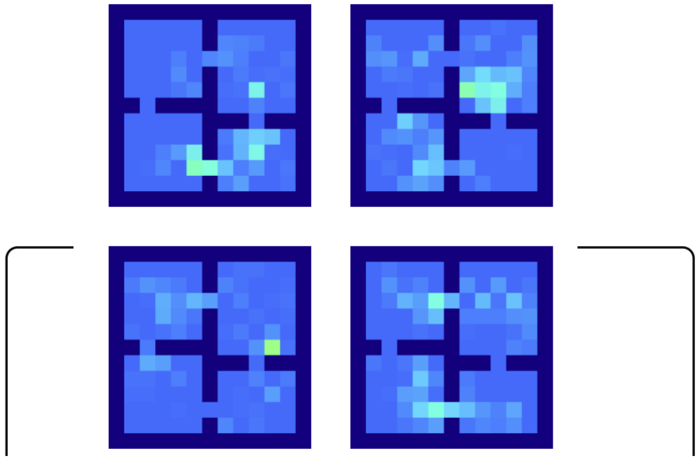


(a) target-seek (easy) (b) target-seek (hard) (c) soccer

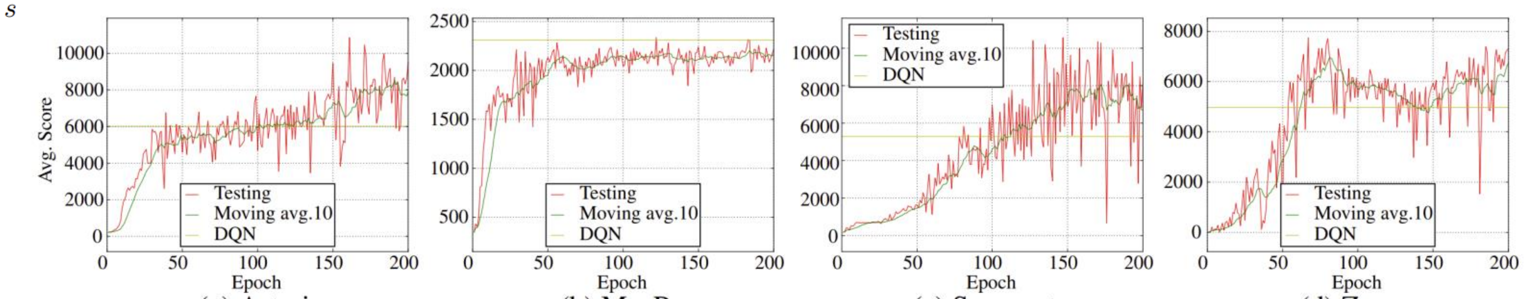
Heess, Wayne, Tassa, Lillicrap, Riedmiller, Silver, **Learning Locomotor Controllers, 2016.**

Option Critic

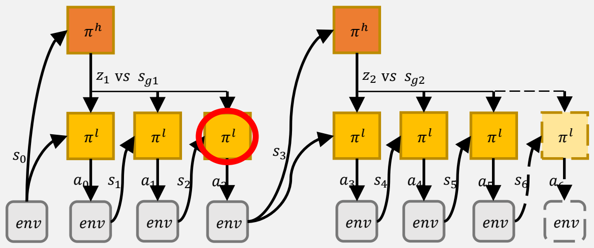
A Markovian option $\omega \in \Omega$ is a triple $(\mathcal{I}_\omega, \pi_\omega, \beta_\omega)$ in which $\mathcal{I}_\omega \subseteq \mathcal{S}$ is an initiation set, π_ω is an *intra-option* policy, and $\beta_\omega : \mathcal{S} \to [0, 1]$ is a termination function. We also assume that $\forall s \in \mathcal{S}, \forall \omega \in \Omega : s \in \mathcal{I}_\omega$ (i.e., all options are available everywhere)



- Option is a self-terminating mini-policy
- Everything trained together with policy gradient



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



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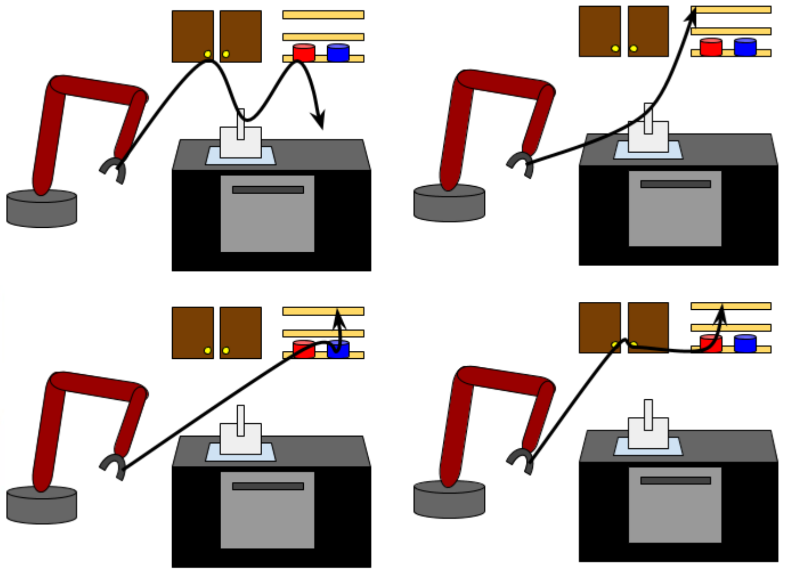
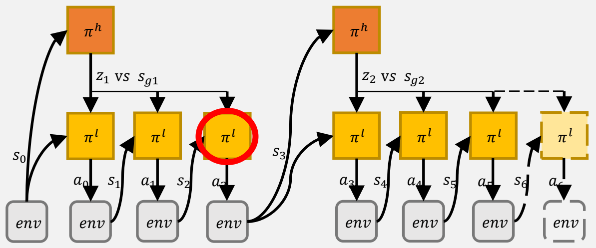
Bacon, Harb, Precup, **The Option-Critic Architecture, 2016.**

Relay Policy Learning





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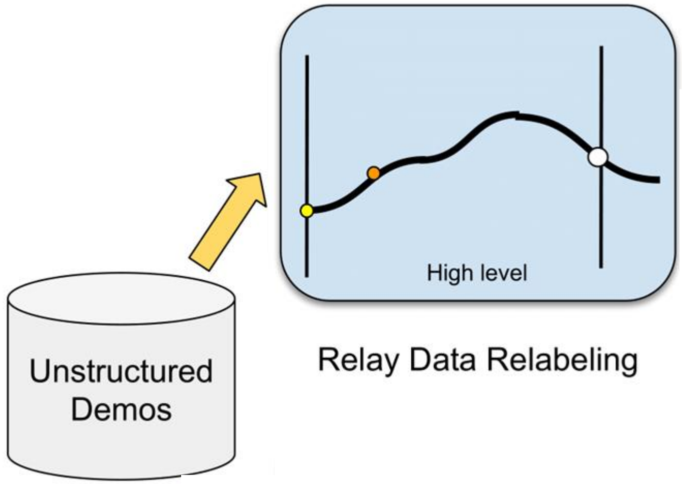
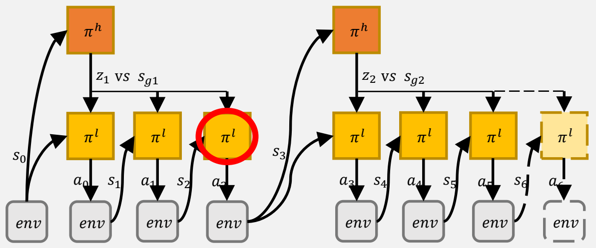
Gupta, Kumar, Lynch, Levine, Hausman, **Relay Policy Learning, 2019.**

Relay Policy Learning





Design choices:

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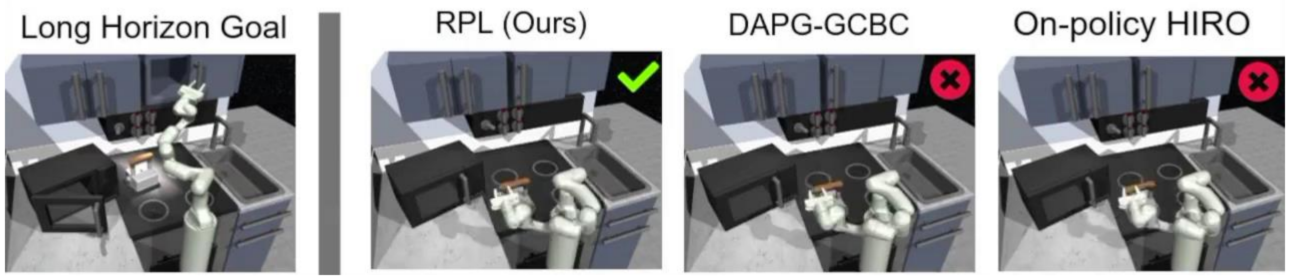
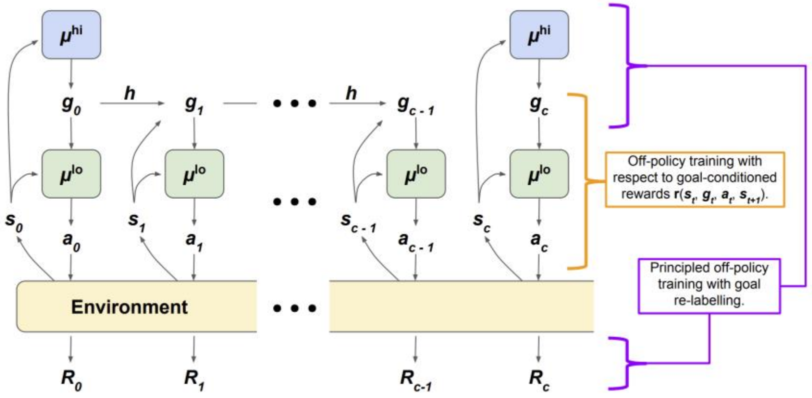
- Goal-conditioned policies with relabeling
- Demonstrations to pre-train everything
- On-policy



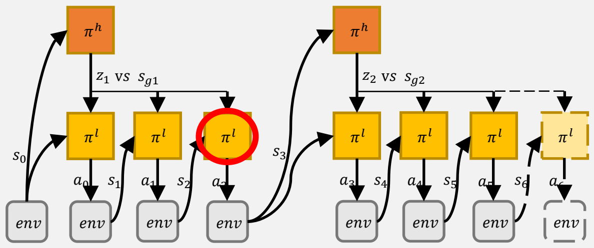
Gupta, Kumar, Lynch, Levine, Hausman, **Relay Policy Learning, 2019.**

HIRO



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.

Figure 2: The design and basic training of HIRO. The lower-level policy interacts directly with the environment. The higher-level policy instructs the lower-level policy via high-level actions, or goals, $g_t \in \mathbb{R}^{d_s}$ which it samples anew every c steps. On intermediate steps, a fixed goal transition function h determines the next step's goal. The goal simply instructs the lower-level policy to reach specific states, which allows the lower-level policy to easily learn from prior off-policy experience.



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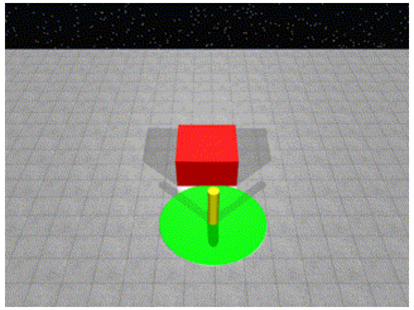
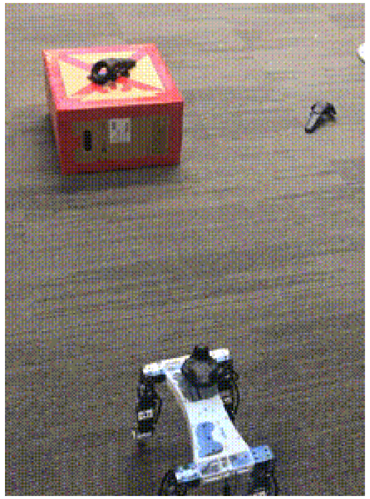
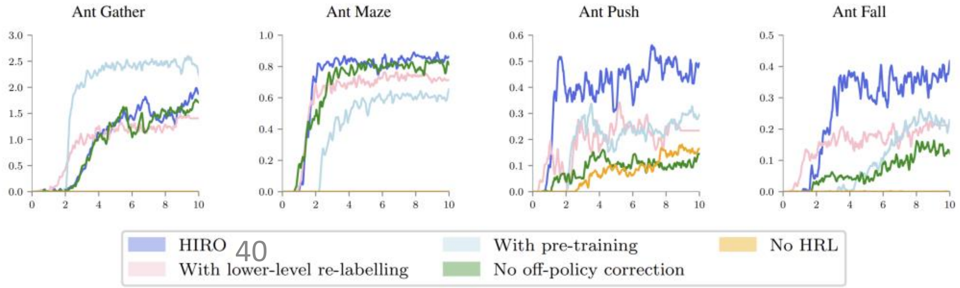




- Goal-conditioned policies with relabeling
- Off-policy training through off-policy corrections



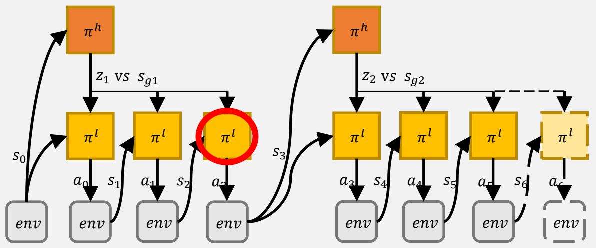
Nachum, Gu, Lee, Levine **HIRO, 2018.**

HRL Summary

- Multiple design choices and frameworks
- Helps with exploration and temporally extended tasks
- Can be difficult to get it to work
- Seems like a natural direction for harder RL problems

Hypothesis	Experiments	Important?
(H1) Temporal training	Figures 2, 3	Yes, but only for the use of multi-step rewards (n-step returns).
(H2) Temporal exploration	Figures 2, 4	Yes, and this is important even for non-hierarchical exploration.
(H3) Semantic training	Figure 3	No.
(H4) Semantic exploration	Figure 4	Yes, and this is important even for non-hierarchical exploration.

Figure 5: A summary of our conclusions on the benefits of hierarchy.



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Nachum, Lang, Lu, Gu, Lee, Levine, Why Does Hierarchy (Sometimes) Work? 2019.

The Plan

Information-theoretic concepts

Skill discovery

Using discovered skills

Hierarchical RL

Next Week

Can the agent **learn continuously** over their life-time?

Lifelong learning – **Nov 4**