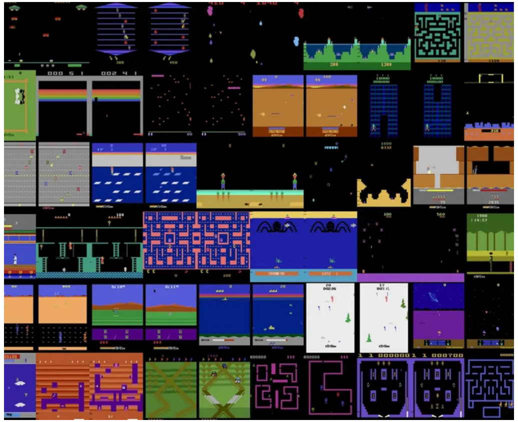
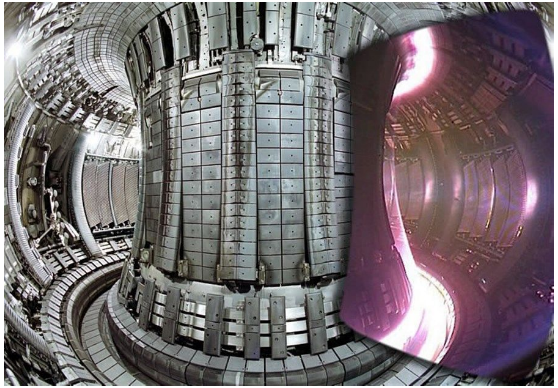
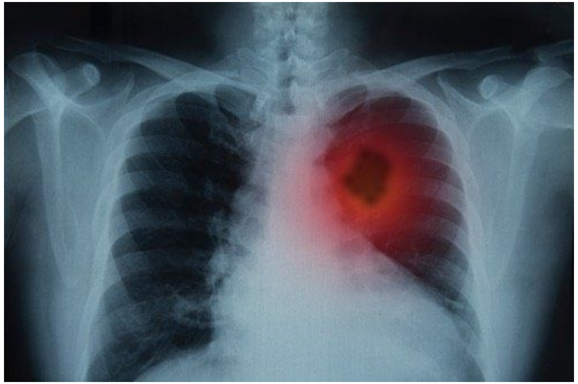
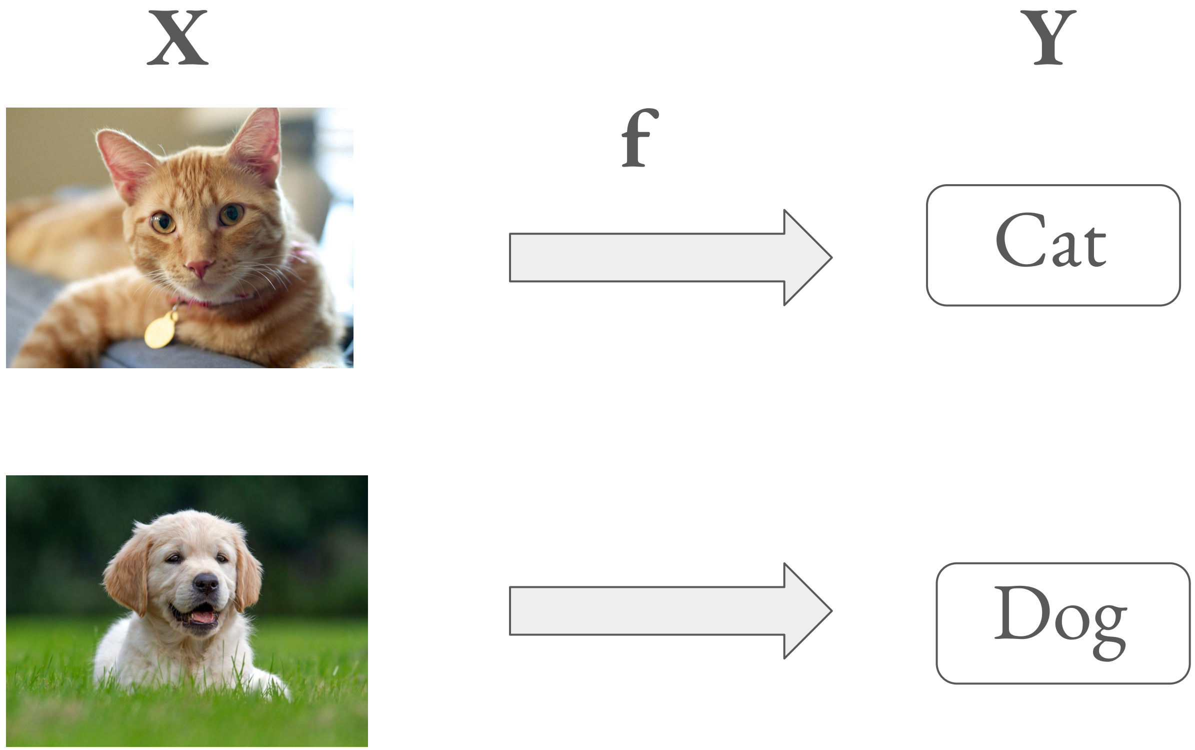
Continual Meta RL

By Kellen Kanarios

Reinforcement Learning


Supervised Learning



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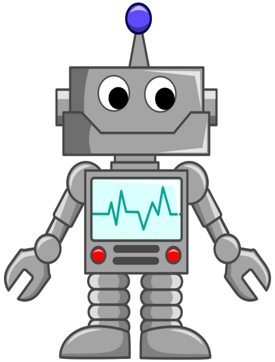

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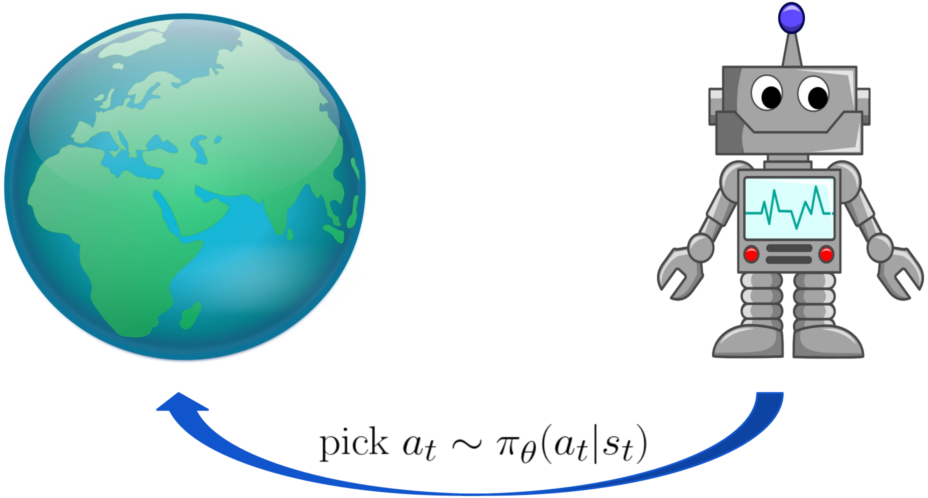

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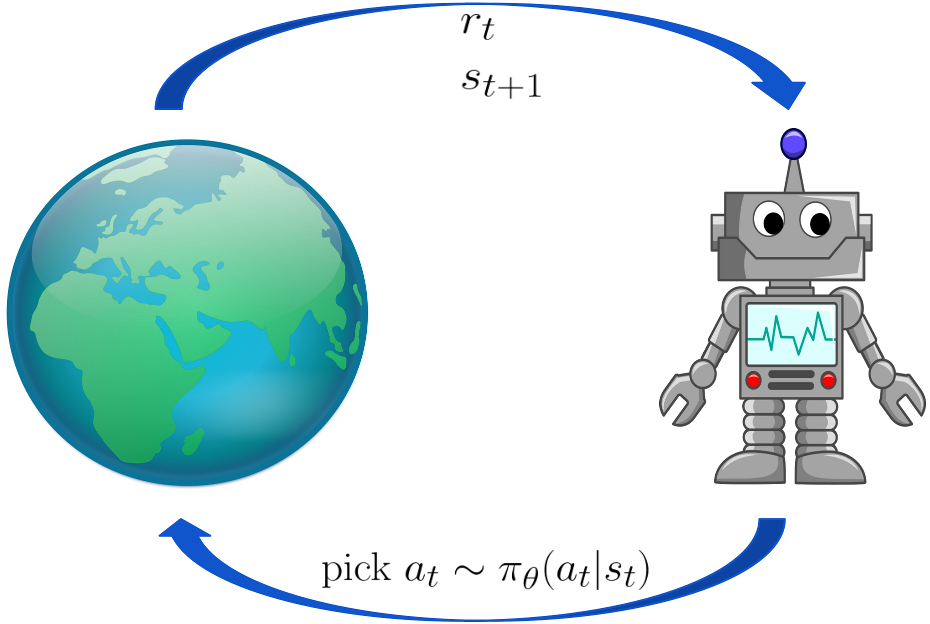

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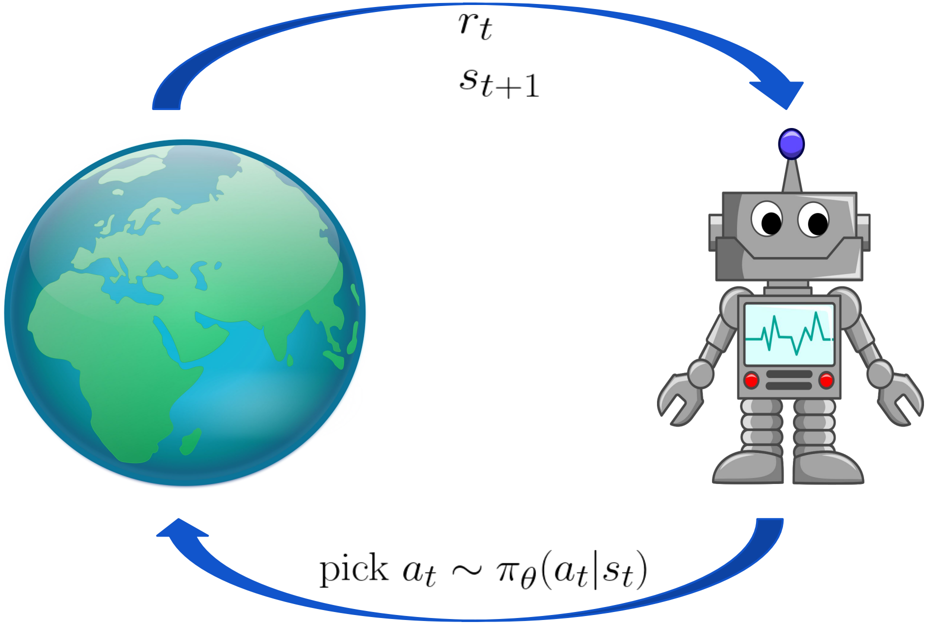
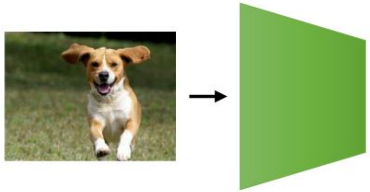


use (s_t, a_t, s_{t+1}, r_t) to improve π_θ

Meta Learning

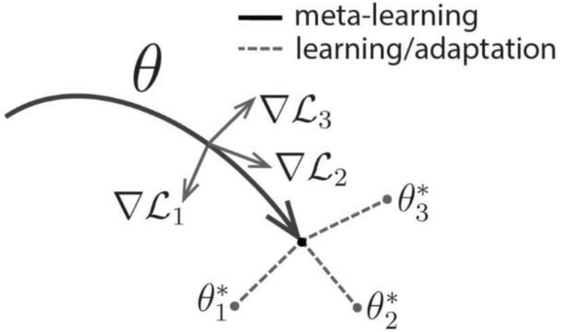
Meta Learning



θ

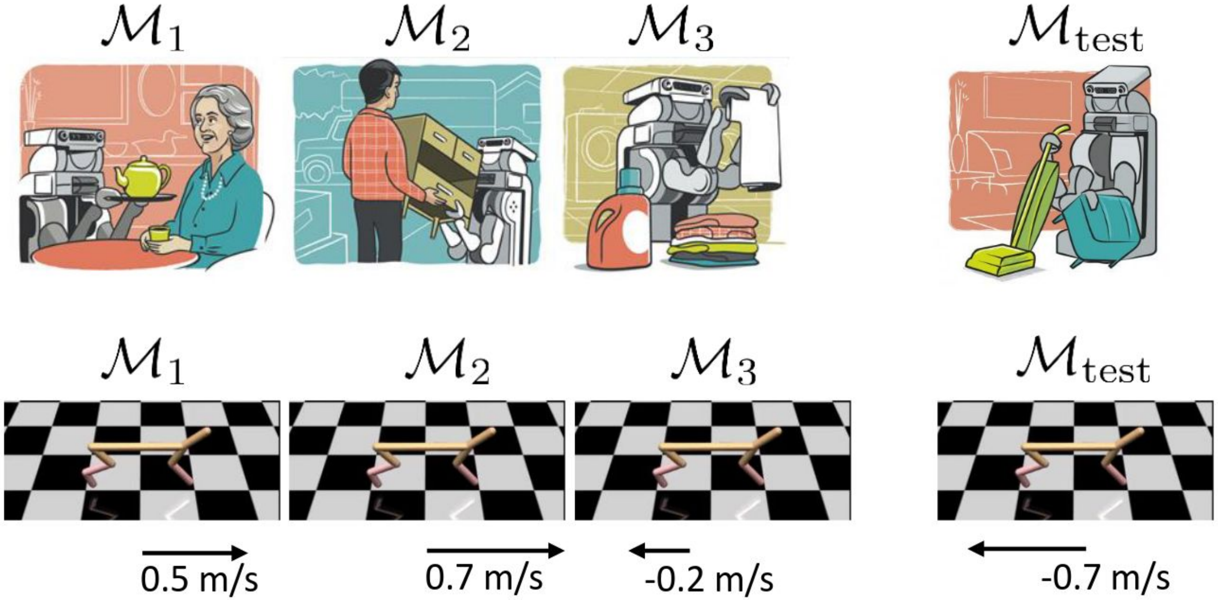
$$\cancel{\theta \leftarrow \theta - \alpha \nabla_\theta \mathcal{L}(\theta, \mathcal{D}^{\mathrm{tr}})}$$

$$\theta \leftarrow \theta - \beta \sum_i \nabla_\theta \mathcal{L}(\theta - \alpha \nabla_\theta \mathcal{L}(\theta, \mathcal{D}_i^{\mathrm{tr}}), \mathcal{D}_i^{\mathrm{ts}})$$



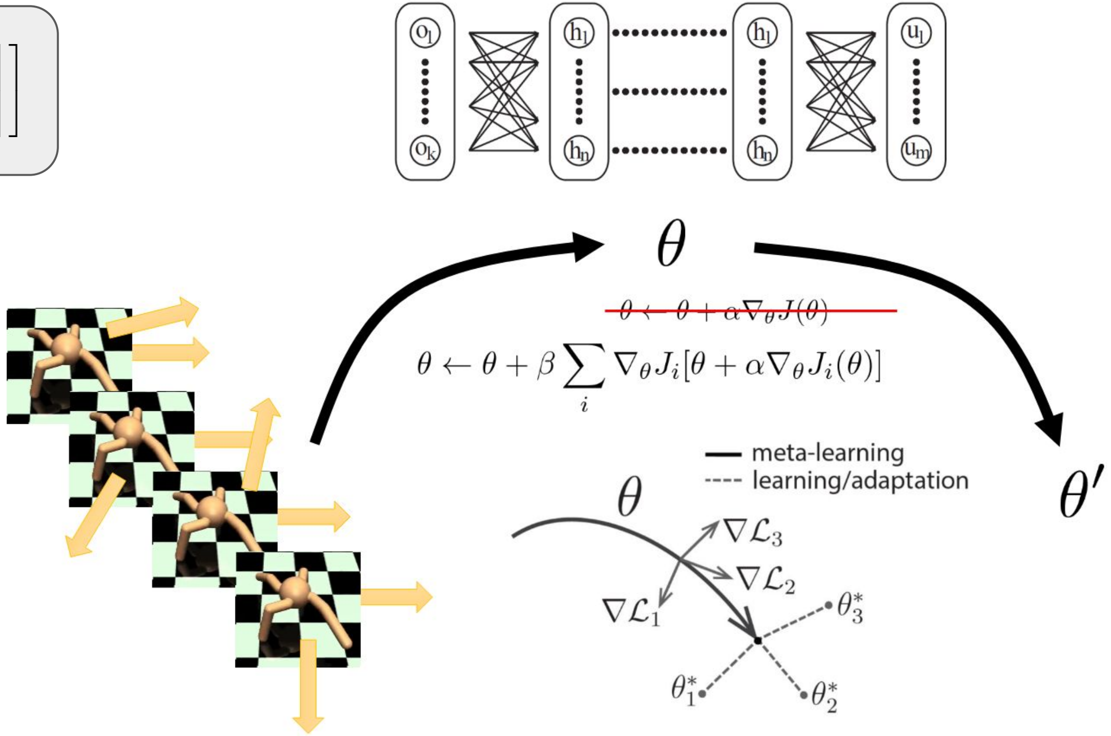
θ'

Meta Reinforcement Learning

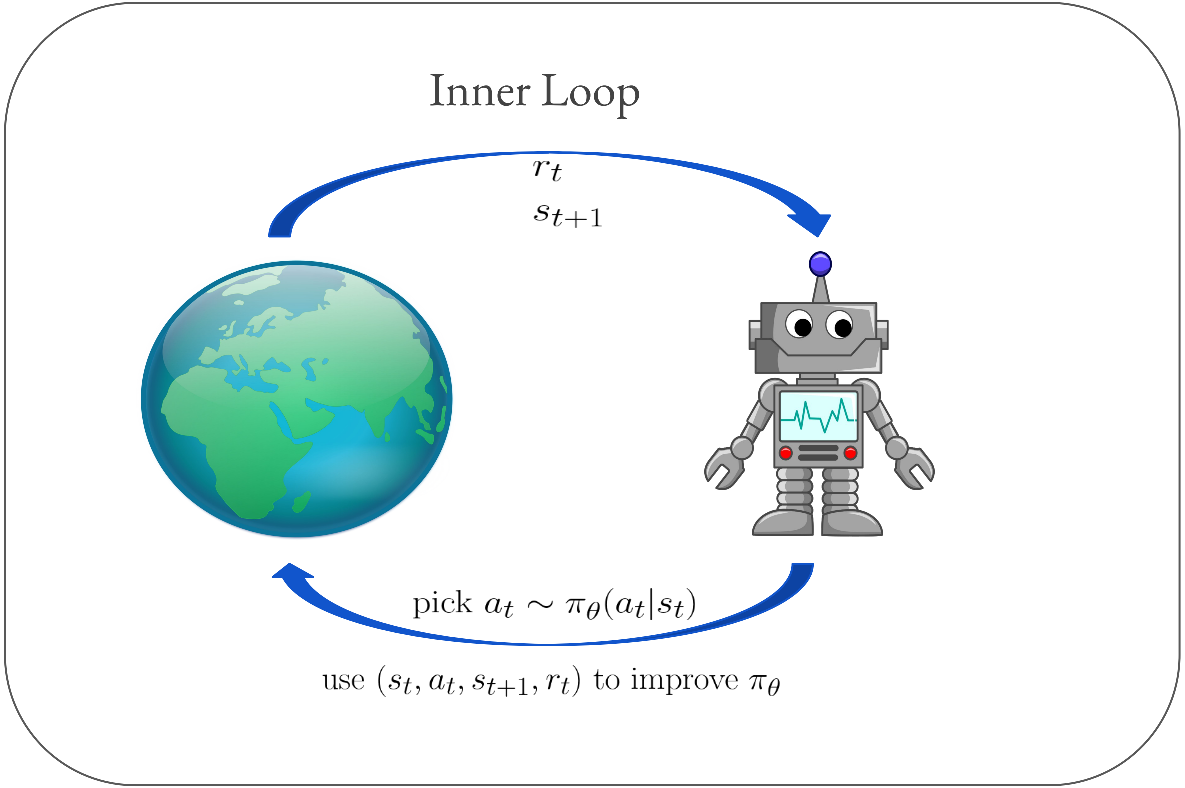


Meta Reinforcement Learning

$$\mathcal{J}(\theta) = \mathbb{E}_{M^i \sim p(\mathcal{M})}\left[\mathbb{E}_{\mathcal{D}}\left[\sum_{\tau \in \mathcal{D}_{K:H}} G(\tau) \middle| f_\theta, \mathcal{M}^i\right]\right]$$



Online Meta Reinforcement Learning



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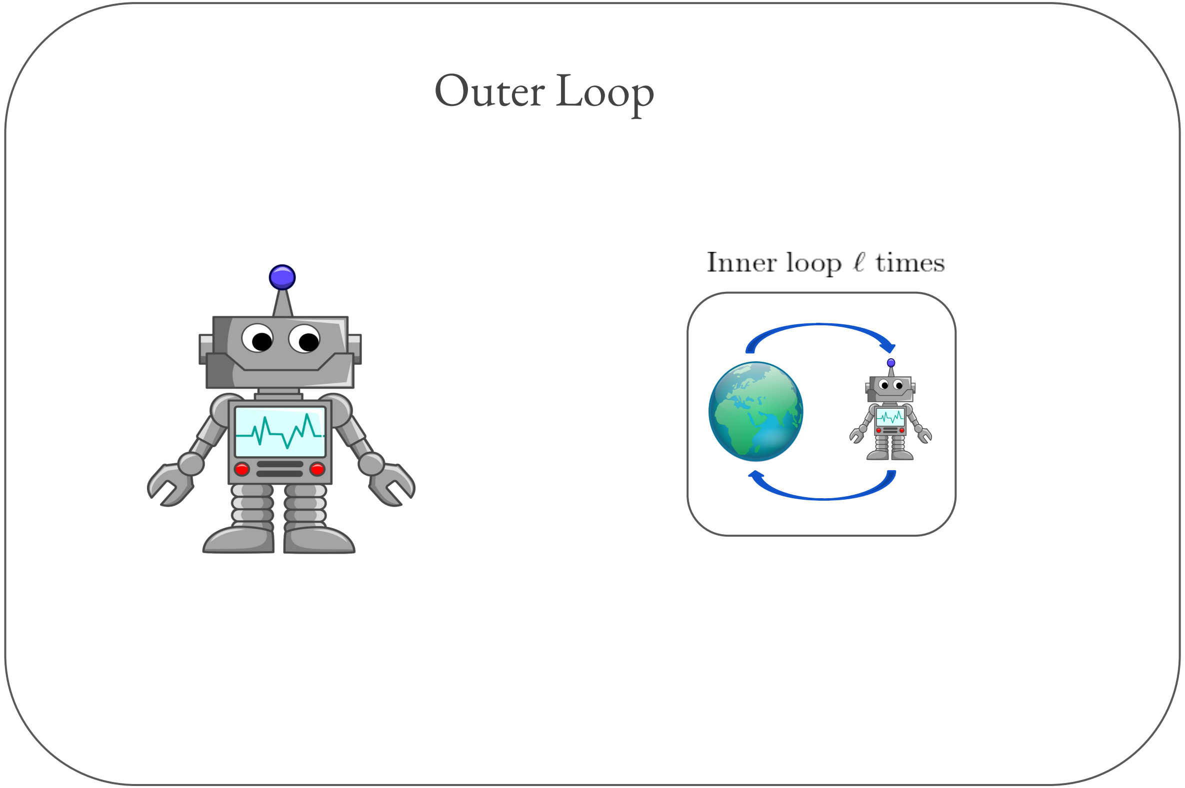

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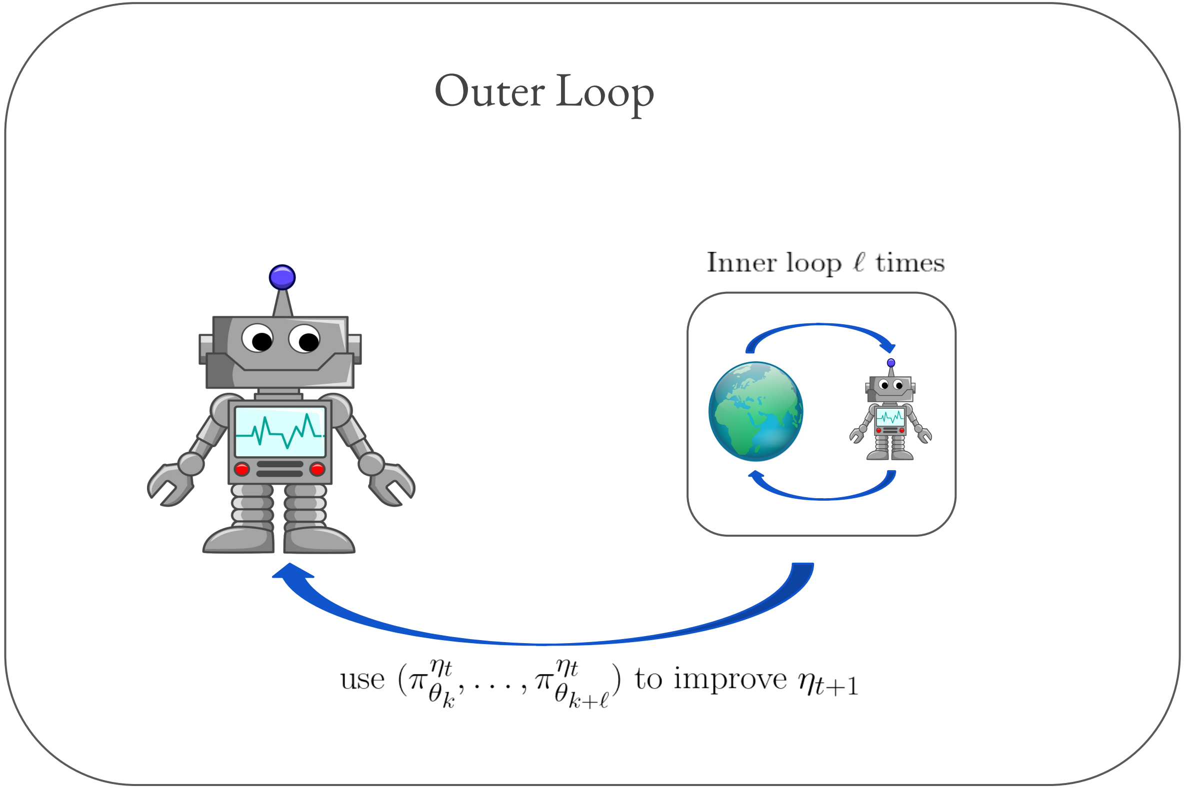

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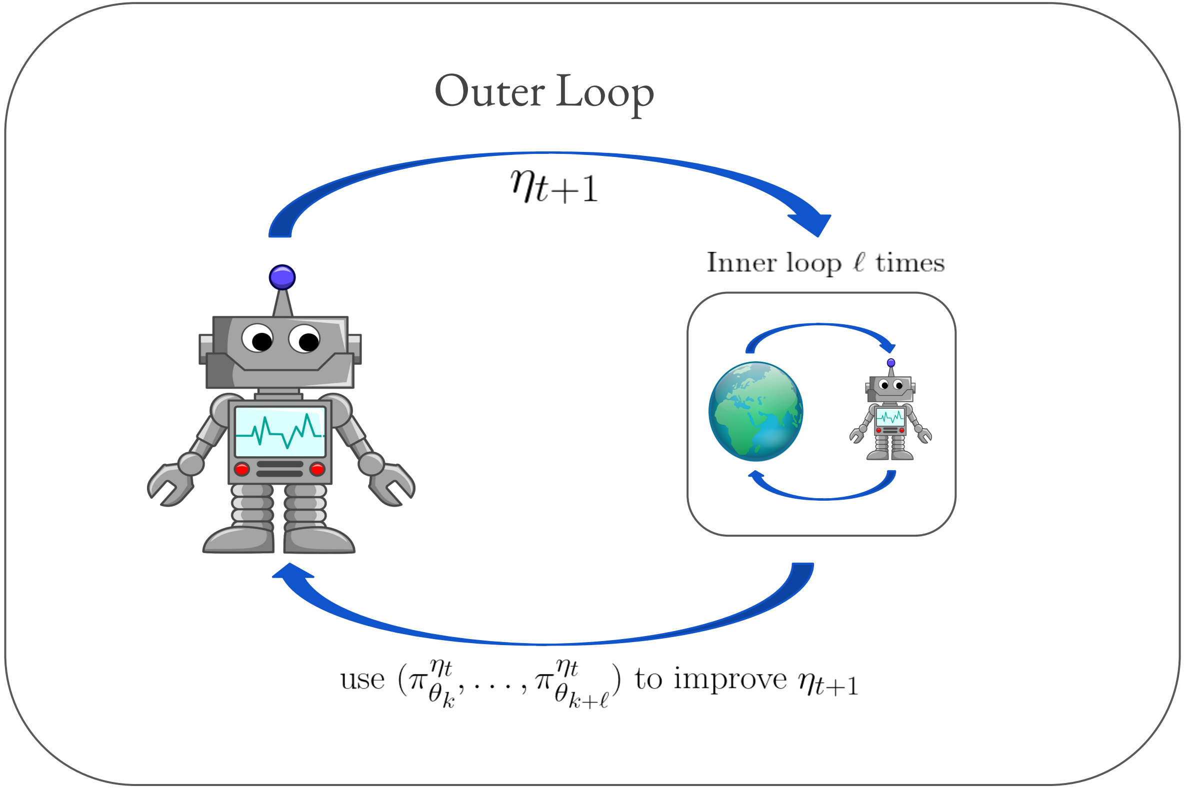
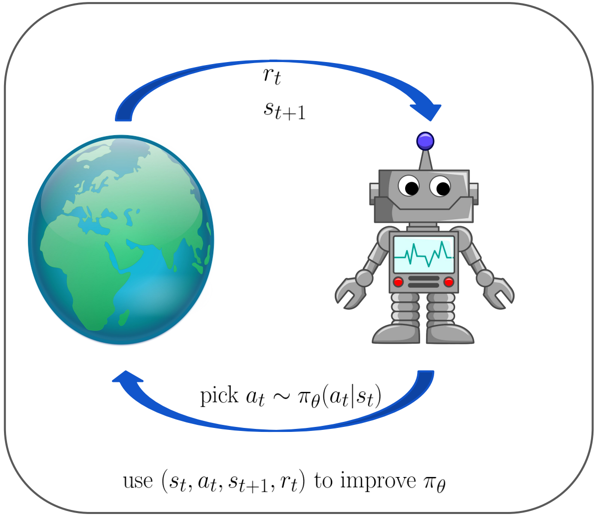
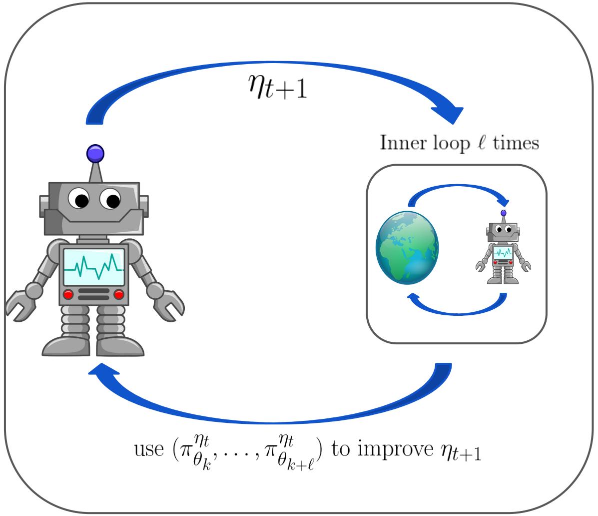


Online Meta Reinforcement Learning

Inner Loop



Outer Loop



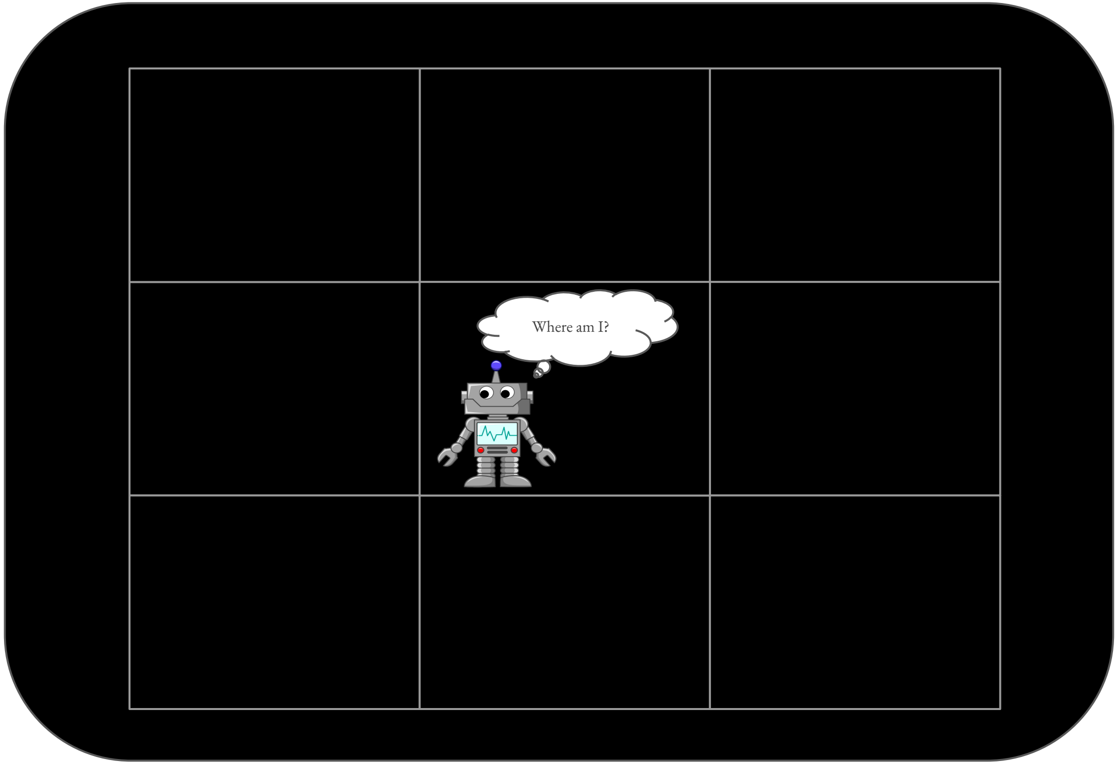
Online Meta Reinforcement Learning

Goal: meta-learn generally useful knowledge

- Learned online as we adapt to the current task.
- Transfers across similar tasks.

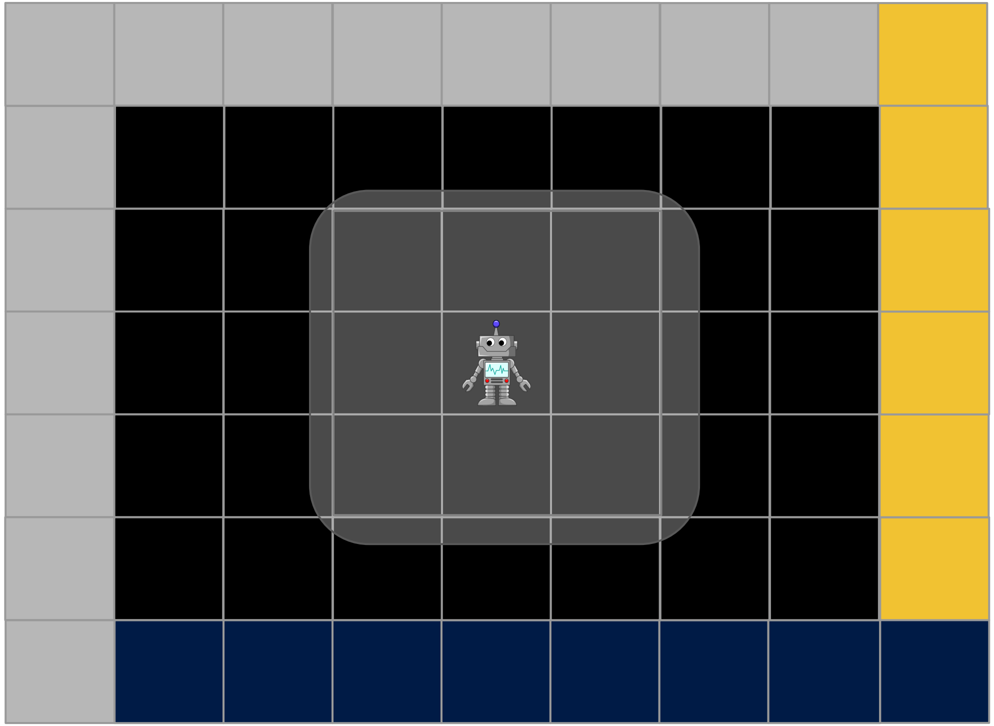
Discovery of Useful Questions (Veeriah et al.)

A Structured State Representation



Veeriah Et al. (2019). Discovery of Useful Questions as Auxiliary Tasks

A Structured State Representation



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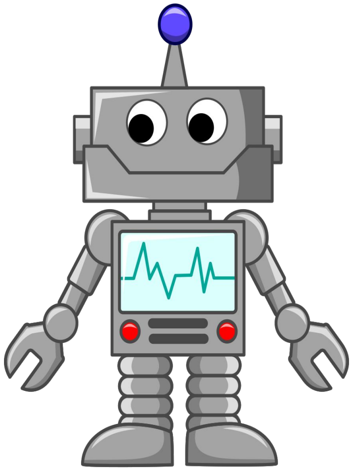
Useful Questions



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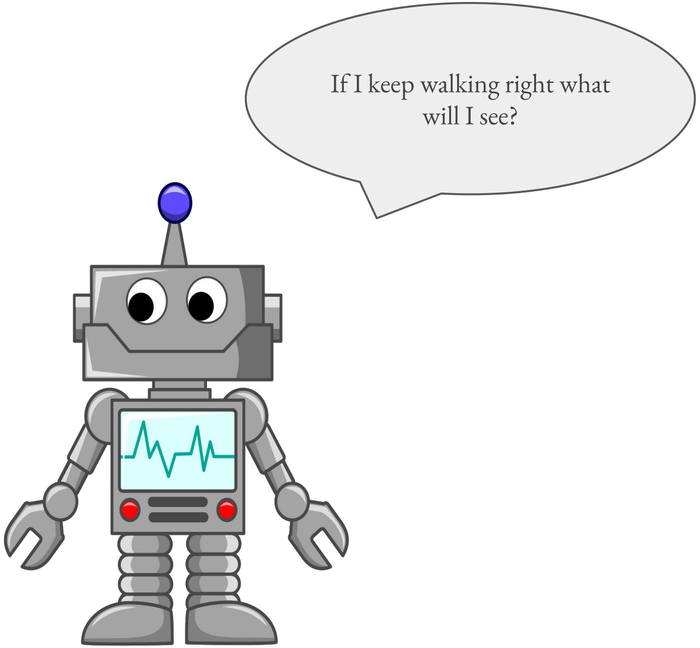

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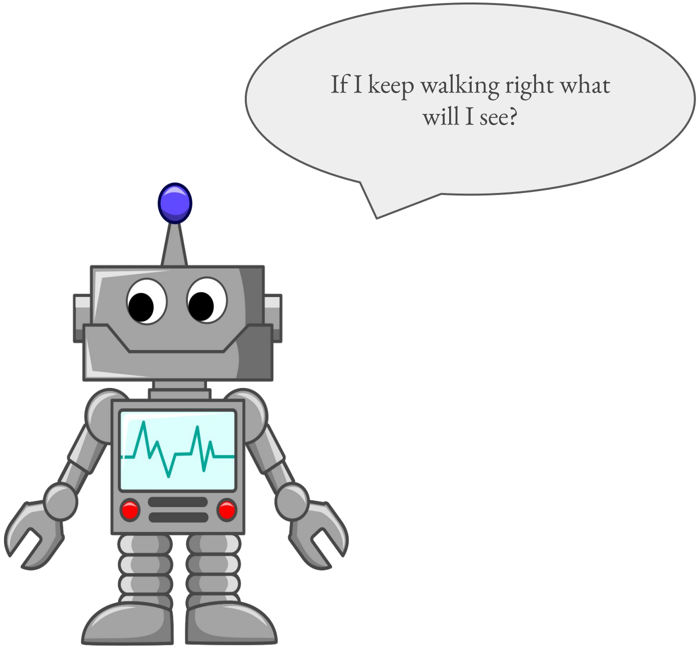

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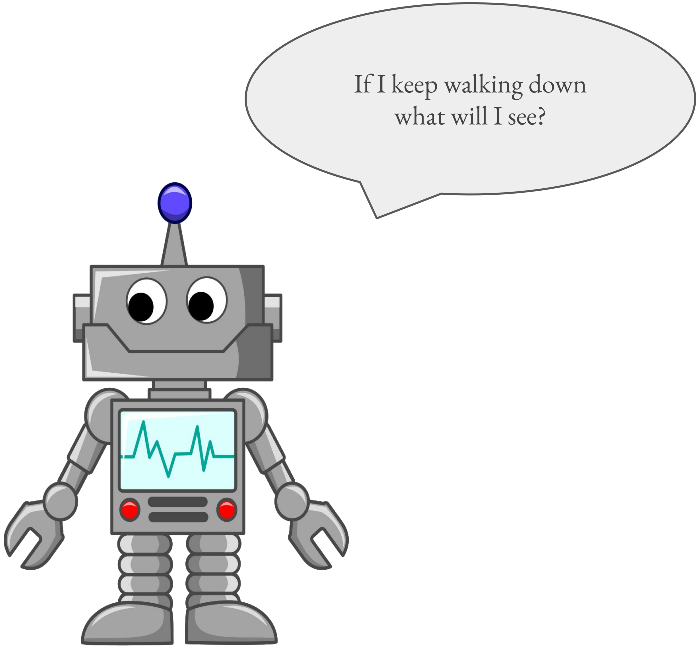

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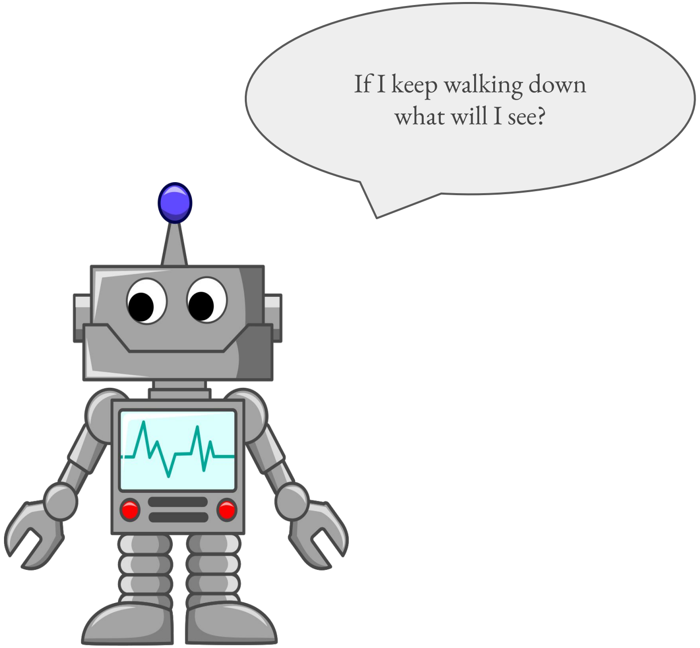

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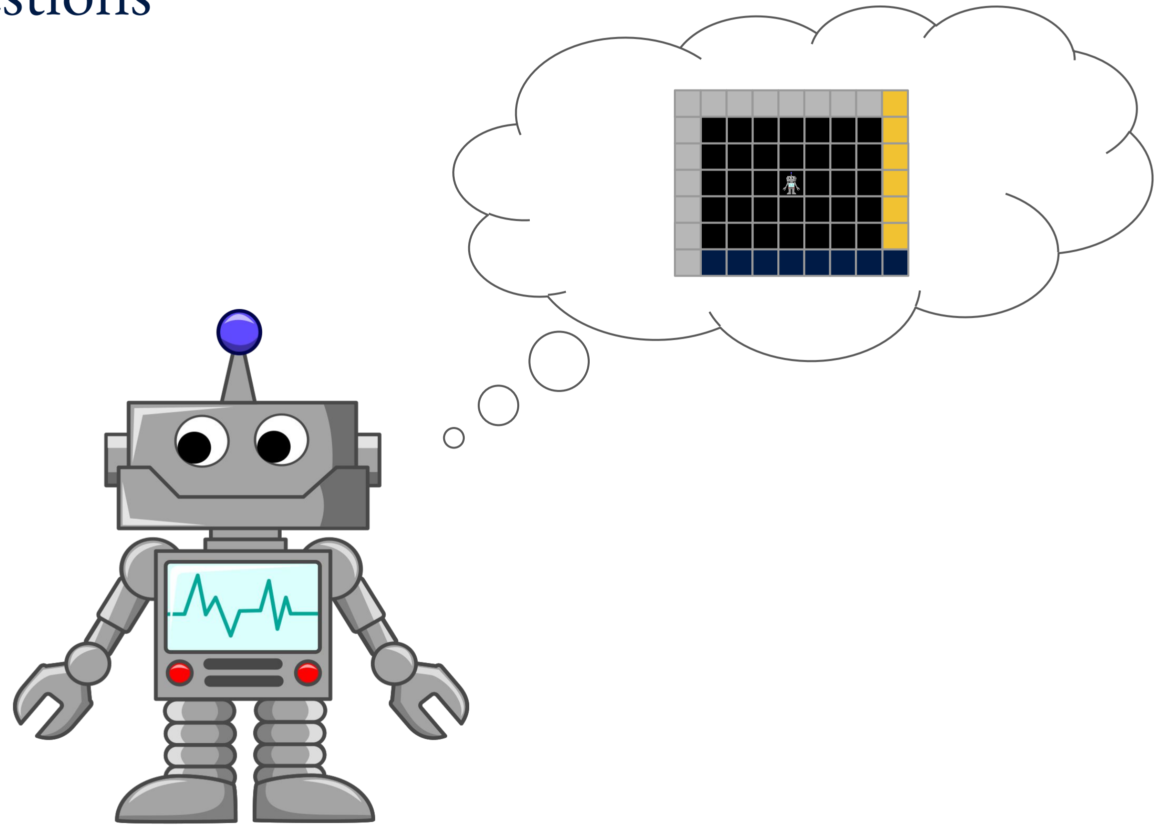

Veeriah Et al. (2019). Discovery of Useful Questions as Auxiliary Tasks

How do we represent predictions?

- General Value Functions (Sutton et al.)

$$V^{\pi,c,\gamma}(s) = \mathbb{E}\Big[\sum_{t=0}^{\infty} \gamma^t c_{t+1} | \pi, c, s_0 = s\Big]$$

cumulant $c : \mathcal{S} \to \mathbb{R}$.

state-dependent discount factor $\gamma : \mathcal{S} \to [0, 1]$

- Can learn using traditional TD methods i.e. GAE, V-trace, etc.

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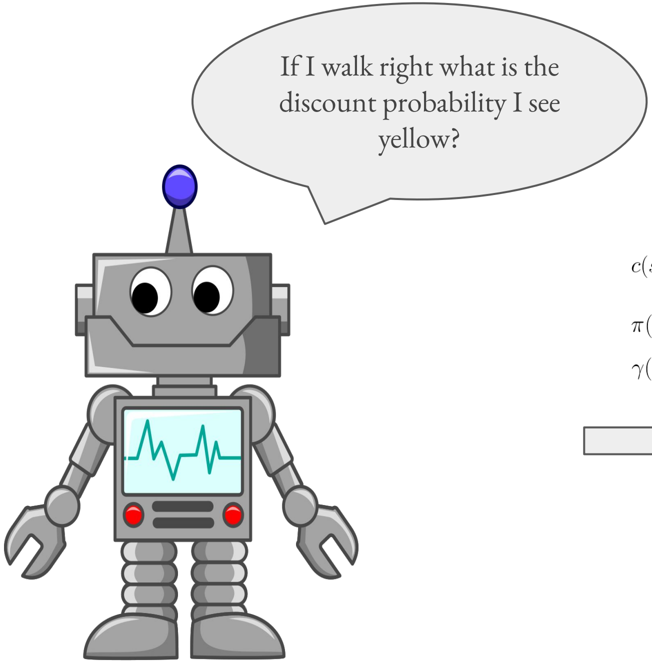
How do we represent predictions?



$$c(s) = \begin{cases} 1, & \text{if yellow} \in s \\ 0, & \text{otherwise.} \end{cases}$$

$$\pi(s) = \text{move right}$$

$$\gamma(s) = 0.9 \text{ (for example)}$$

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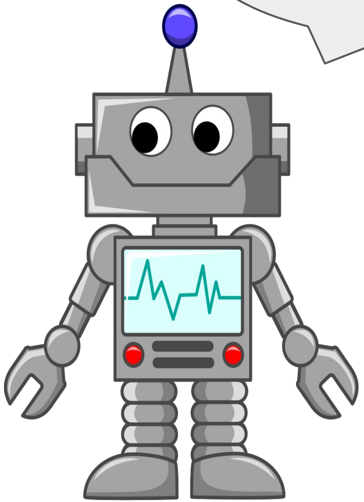
How do we represent predictions?

If I walk right what is the discount probability I see yellow?



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$$V^{\pi,\gamma,c}(s)$$

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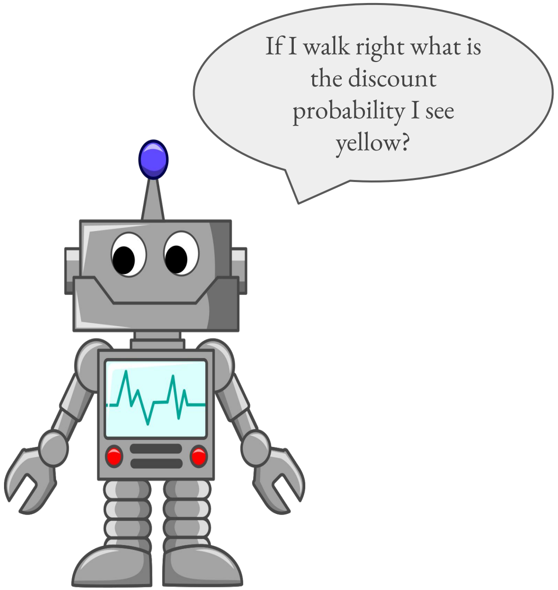

	0.53	0.59	0.66	0.73	0.81	0.9	1	
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	0.53	0.59	0.66	0.73	0.81	0.9	1	
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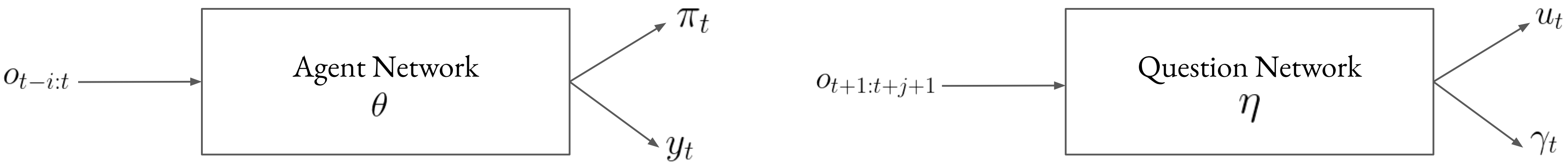
How do we learn useful questions?



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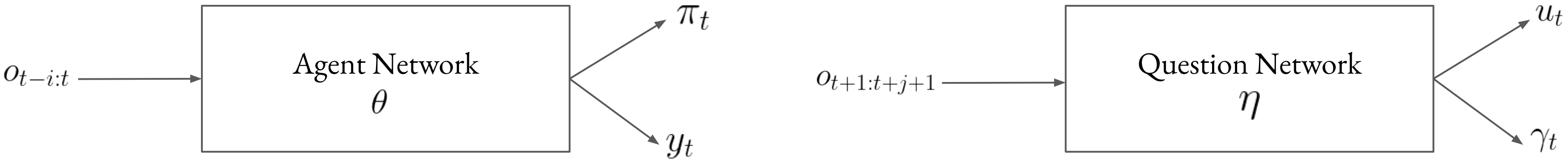

$$-\alpha \nabla_{\theta^{y_i}} \mathcal{L}^{ans} = \alpha\big(G_t^{y_i} - y_i(x_t)\big)\nabla_{\theta_i^y} y_i(x_t)$$

$$\theta_{t,k} \leftarrow \theta_{t,k-1} - \alpha'\nabla_{\theta_{t,k-1}}\mathcal{L}^{RL}(\theta_{t,k-1}) - \alpha'\nabla_{\theta_{t,k-1}}\mathcal{L}^{ans}(\theta_{t,k-1}).$$

$$\eta_{t+1} \leftarrow \eta_t - \alpha\nabla_\eta \sum_{k=1}^{L}\mathcal{L}^{RL}(\theta_{t,k}).$$

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How do we learn useful questions?

$\theta_{t,k}$

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How do we learn useful questions?

$$\theta_{t,k} \longrightarrow \theta_{t,k+1}$$

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Inner Update: $\longrightarrow$

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How do we learn useful questions?

$$\theta_{t,k} \longrightarrow \theta_{t,k+1} \longrightarrow \cdots \longrightarrow \theta_{t,k+n}$$

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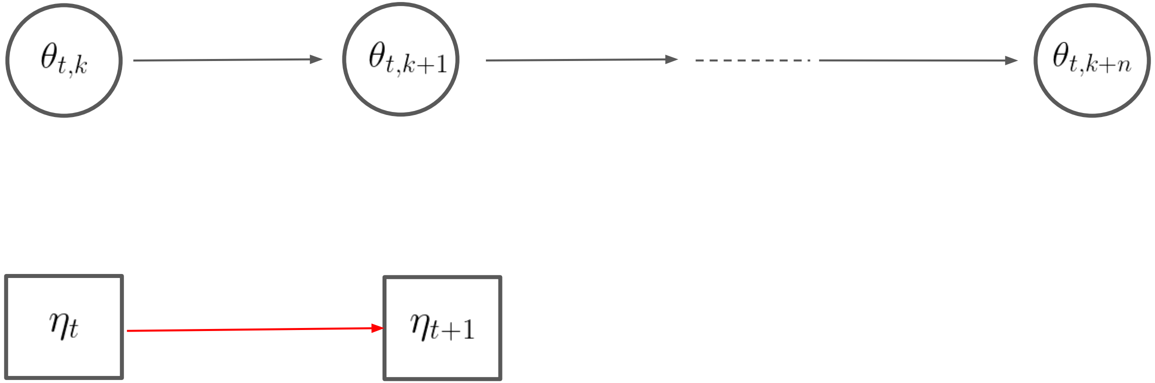

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Inner Update:

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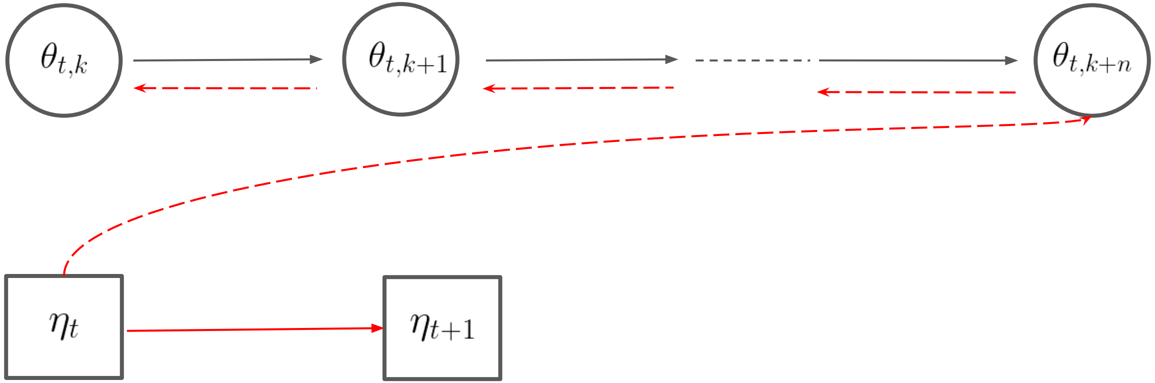

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Inner Update:

Outer Update:

Gradient Flow:

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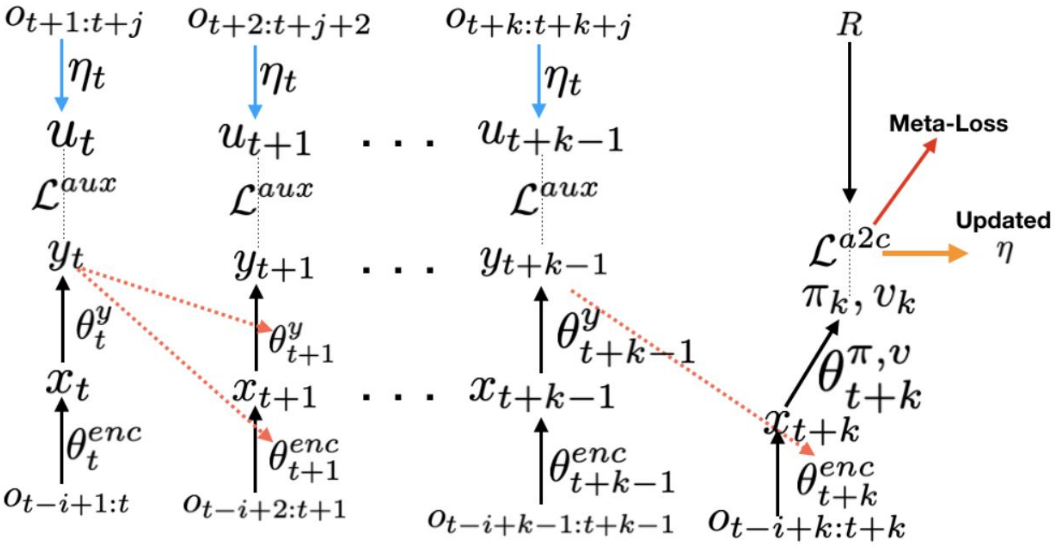

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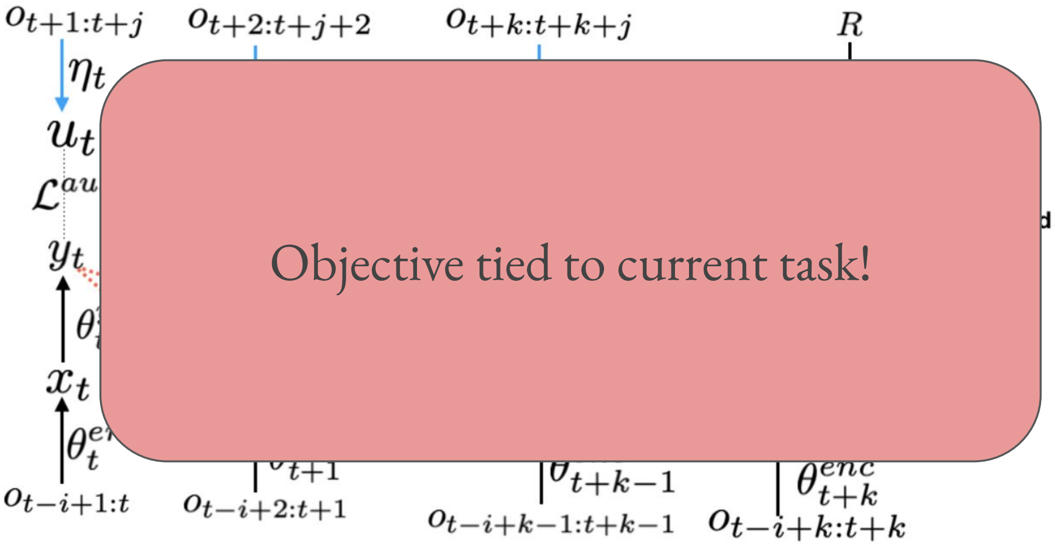

Objective tied to current task!

Veeriah Et al. (2019). Discovery of Useful Questions as Auxiliary Tasks

Decoupling Task Objective

- Meta objective based on learning dynamics
- **Idea**: Future policy will be better than current one

Flennerhag Et al. (2018). Bootstrapped Meta Learning

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- **Idea**: Future policy will be better than current one

Bootstrapped **M**eta **G**radient (**BMG**):

$$\mathcal{L}_{\text{outer}} = \text{KL}(\pi_{\theta_{t+K(\eta)}} || \pi_{\theta_{t+K+L}}),$$

Flennerhag Et al. (2018). Bootstrapped Meta Learning

Non-Stationarity

Answer targets are constantly changing

- Plasticity Loss

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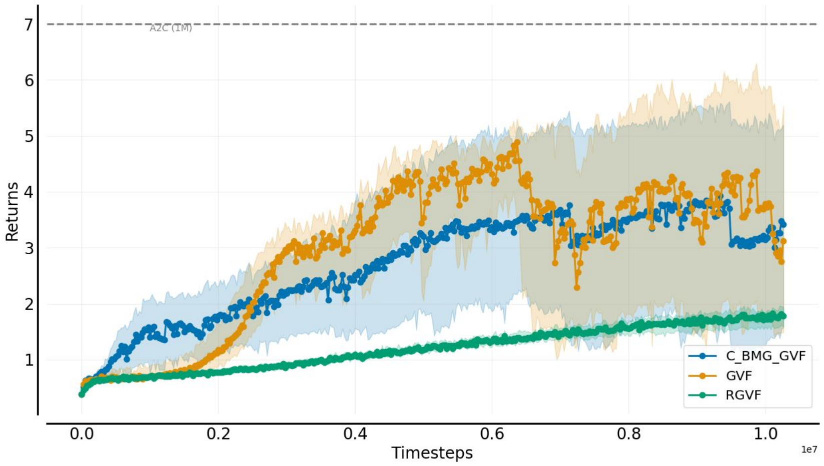
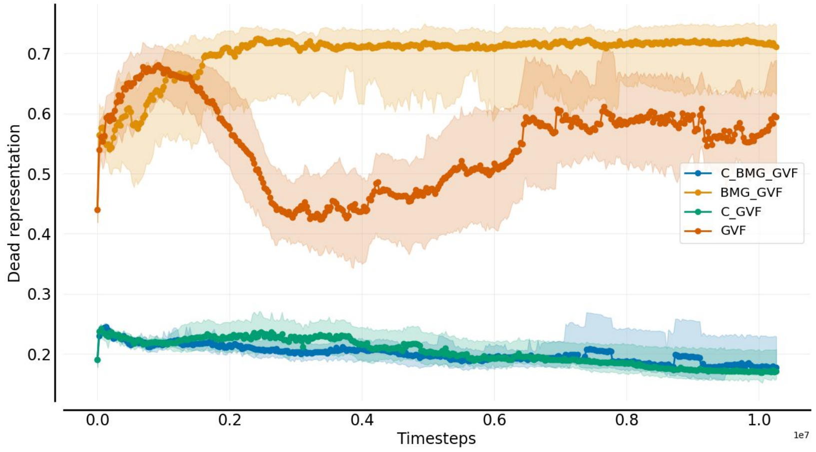
Concatenated **Re**ctified **L**inear **U**nit

$$\mathrm{CReLU}(x) = [\mathrm{ReLU}(x),\ \mathrm{ReLU}(-x)]$$

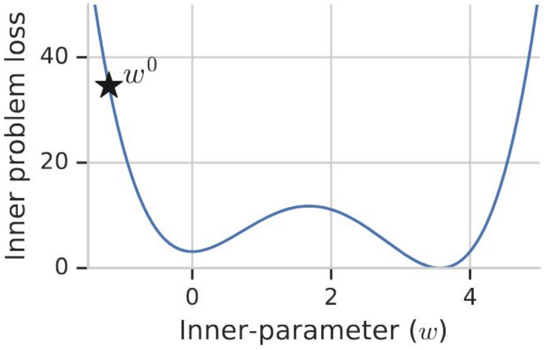
Experiments

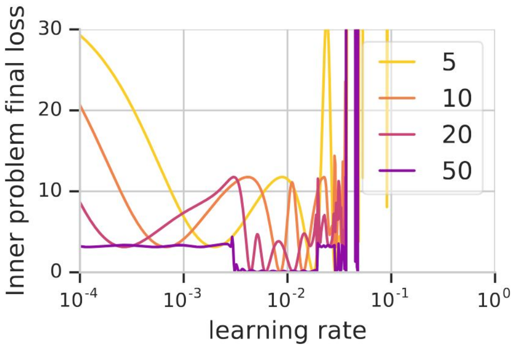


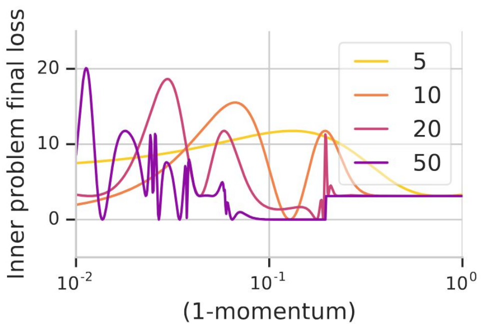


Meta RL Is HARD!

- Truncated backprop
- Evolutionary strategies







Metz et al. (2019). Understanding and correcting pathologies in the training of learned optimizers

Continual RL: Where to go from here?

What does it mean to learn continually?

"A continual learning agent is an agent that never stops learning" - ***Abel et al.***

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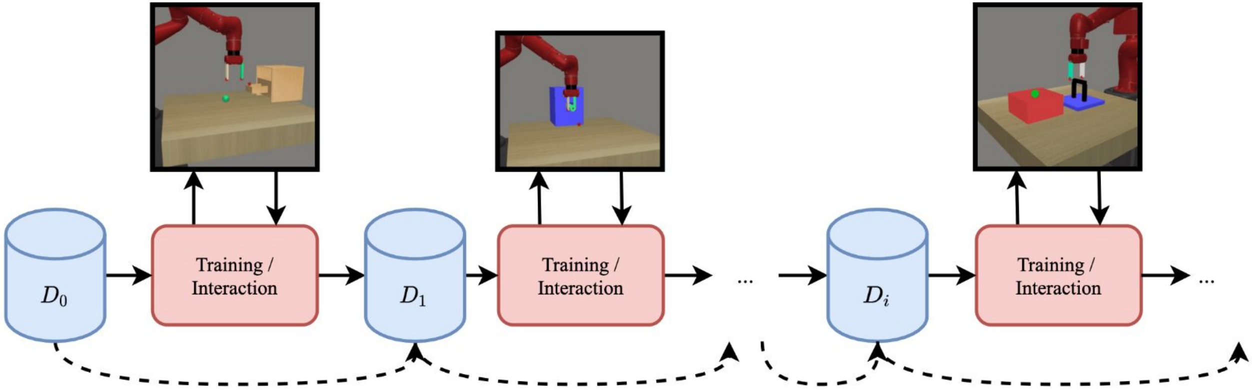
"A continual learning agent is an agent that never stops learning" - ***Abel et al.***

In practice:

- No known task distribution a priori.
- Tasks are encountered sequentially and may or may not be seen again.



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In practice:

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What we want:

- Given a sufficient amount of samples in each task learn the optimal policy for each task -> **Plasticity.**
- Perform "better" on previously learned tasks -> **Minimizing Catastrophic Forgetting/Interference.**
- Similar "structure" to a previous task better performance -> **Forward Transfer.**

Forward Transfer: Off Policy GVF

- GVFs are learned on policy in previous method.

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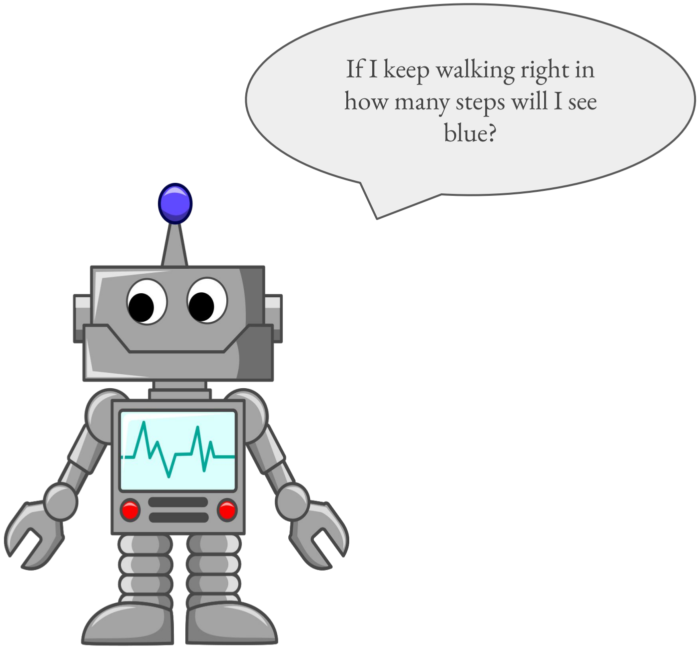

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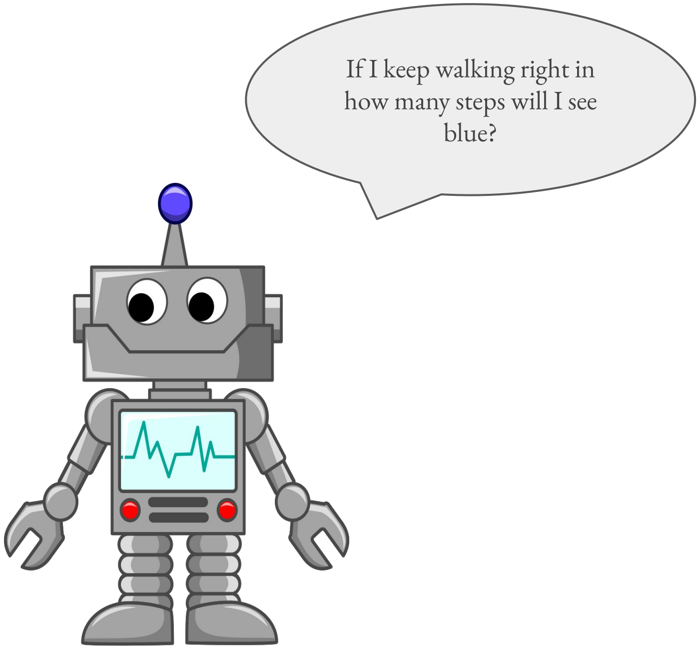

Continual Auxiliary Tasks: Successor Features

Linear MDP Assumption: Can decompose reward as $r_t = \langle \phi(s_t, a_t), w \rangle$

Barreto Et al. (2016). Successor Features for Transfer in Reinforcement Learning

Continual Auxiliary Tasks: Successor Features

Linear MDP Assumption: Can decompose reward as $r_t = \langle \phi(s_t, a_t), w \rangle$

- Assumed to be given *cumulant* $\phi : \mathcal{S} \times \mathcal{A} \to \mathbb{R}^d$
- $w \in \mathbb{R}^d$ encodes the task representation
- We learn a *successor feature* $\psi(s_t, a_t)$ via bootstrapping $\psi(s_t, a_t) = \phi(s_t, a_t) + \gamma \psi(s_{t+1}, a^*)$
- Then we have that $\langle \psi(s_t, a_t), w \rangle = Q(s_t, a_t)$
- Then we can quickly learn GVFs of new tasks via learning new w

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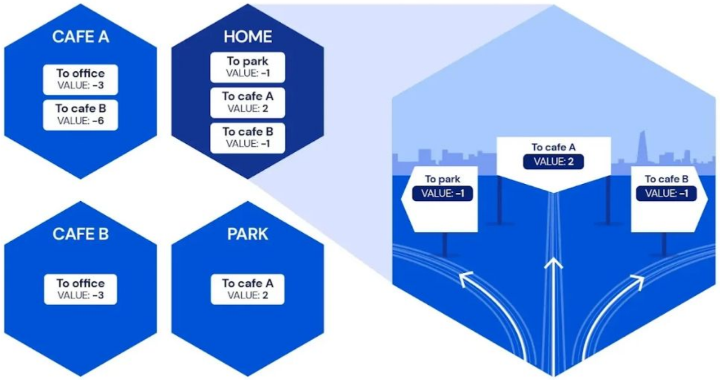

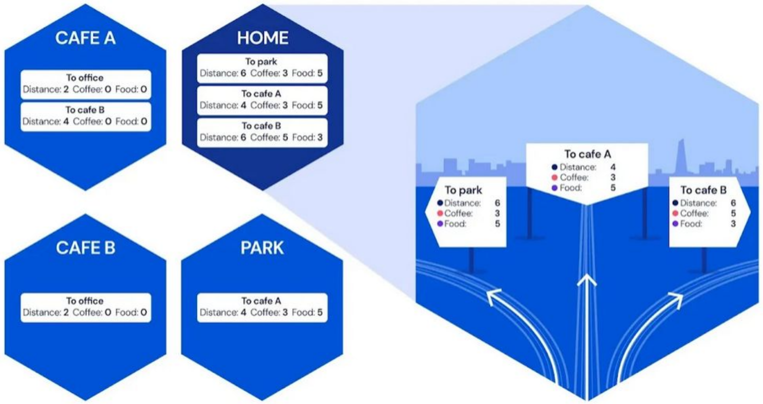

Barreto Et al. (2016). Successor Features for Transfer in Reinforcement Learning

Continual Auxiliary Tasks: Successor Features

Universal Successor Feature Approximator:

- Learn task conditioned successor feature approximator $\boldsymbol{\psi}(s, a, \boldsymbol{w})$
- Can learn optimal off policy $\boldsymbol{\psi}(s_t, a_t, \boldsymbol{w}) = \boldsymbol{\phi}(s_t) + \gamma\boldsymbol{\psi}(s_{t+1}, a^*, \boldsymbol{w})$

Borsa Et al. (2018). Universal Successor Feature Approximators

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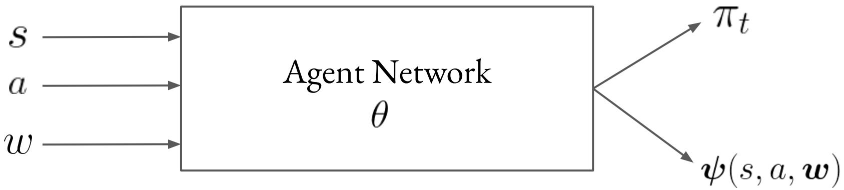
Universal Successor Feature Approximator:

- Learn task conditioned successor feature approximator $\boldsymbol{\psi}(s, a, \boldsymbol{w})$
- Can learn optimal off policy $\boldsymbol{\psi}(s_t, a_t, \boldsymbol{w}) = \boldsymbol{\phi}(s_t) + \gamma \boldsymbol{\psi}(s_{t+1}, a^*, \boldsymbol{w})$



$$\min_{w} \|r(s_t, a_t) - \langle \boldsymbol{\phi}(s_t, a_t), \boldsymbol{w} \rangle\|$$

Borsa Et al. (2018). Universal Successor Feature Approximators

Off Policy: Deadly Triad

- If target bootstrap at s_1 increases θ then bootstrap target also increases
- Causes divergence when s_2 not visited by behavior policy

Espeholt et al. (2018). IMPALA: Scalable Distributed Deep-RL with Importance Weighted Actor-Learner Architectures

Off Policy: Deadly Triad

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V-Trace:

$$\delta_t V = \rho_t(r_t + \gamma V(x_{t+1}) - V(x_t))$$

$$\rho_t = \min\left(\bar{\rho}, \frac{\pi(a_t|x_t)}{\mu(a_t|x_t)}\right)$$

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$$v_s \stackrel{\text{def}}{=} V(x_s) + \sum_{t=s}^{s+n-1} \gamma^{t-s} \left(\prod_{i=s}^{t-1} c_i\right) \delta_t V \qquad c_i = \min\left(\bar{c}, \frac{\pi(a_i|x_i)}{\mu(a_i|x_i)}\right)$$

Espeholt et al. (2018). IMPALA: Scalable Distributed Deep-RL with Importance Weighted Actor-Learner Architectures

Catastrophic Forgetting

$$\min_{\theta_0^j} \left(\sum_{i=1}^{t} \left(\ell_i \left(\theta_0^j \right) \right) - \alpha \sum_{p,q \leq t} \left(\frac{\partial \ell_p \left(\theta_0^j \right)}{\partial \theta_0^j} \cdot \frac{\partial \ell_q \left(\theta_0^j \right)}{\partial \theta_0^j} \right) \right)$$

Matthew Riemer et al. (2019) Learning to Learn without Forgetting by Maximizing Transfer and Minimizing Interference.

Catastrophic Forgetting

$$\min_{\theta_0^j}\left(\sum_{i=1}^{t}\left(\ell_i\left(\theta_0^j\right)\right)-\alpha\sum_{p,q\leq t}\left(\frac{\partial\ell_p\left(\theta_0^j\right)}{\partial\theta_0^j}\cdot\frac{\partial\ell_q\left(\theta_0^j\right)}{\partial\theta_0^j}\right)\right)$$

Forward Transfer

$$\frac{\partial\ell_p\left(\theta_0^j\right)}{\partial\theta_0^j}\cdot\frac{\partial\ell_q\left(\theta_0^j\right)}{\partial\theta_0^j}>0$$

Catastrophic Interference

$$\frac{\partial\ell_p\left(\theta_0^j\right)}{\partial\theta_0^j}\cdot\frac{\partial\ell_q\left(\theta_0^j\right)}{\partial\theta_0^j}<0$$

Matthew Riemer et al. (2019) Learning to Learn without Forgetting by Maximizing Transfer and Minimizing Interference.

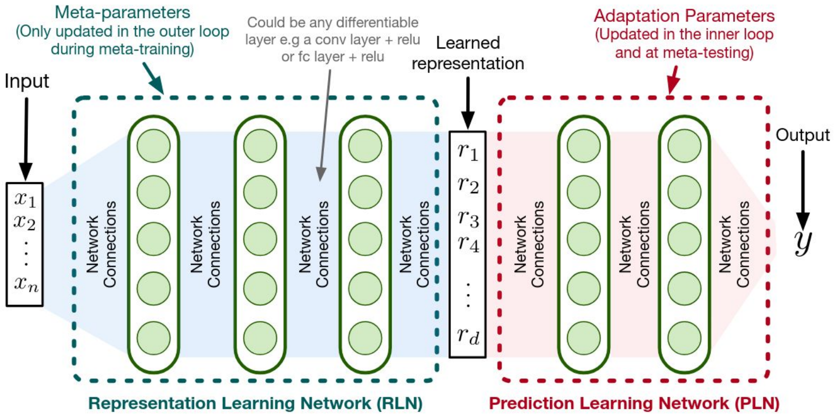
Catastrophic Forgetting

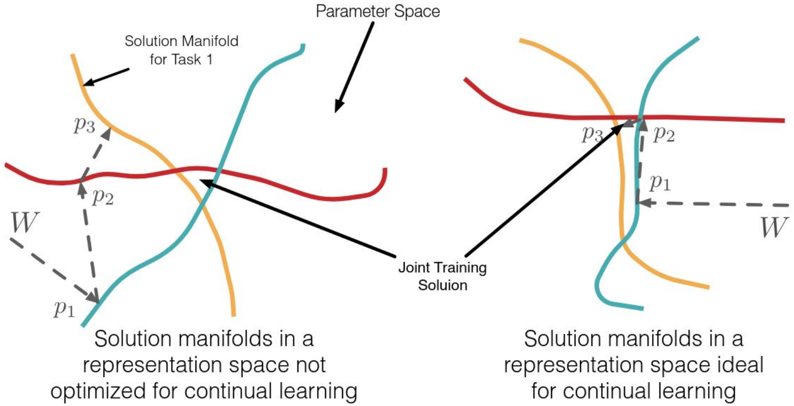
$$\min_{\theta_0^j} \left(\sum_{i=1}^{t} \left(\ell_i \left(\theta_0^j \right) \right) - \alpha \sum_{p,q \leq t} \left(\frac{\partial \ell_p \left(\theta_0^j \right)}{\partial \theta_0^j} \cdot \frac{\partial \ell_q \left(\theta_0^j \right)}{\partial \theta_0^j} \right) \right)$$

Problem: No access to ℓ_i in continual RL

Matthew Riemer et al. (2019) Learning to Learn without Forgetting by Maximizing Transfer and Minimizing Interference.

Catastrophic Forgetting: Intuition

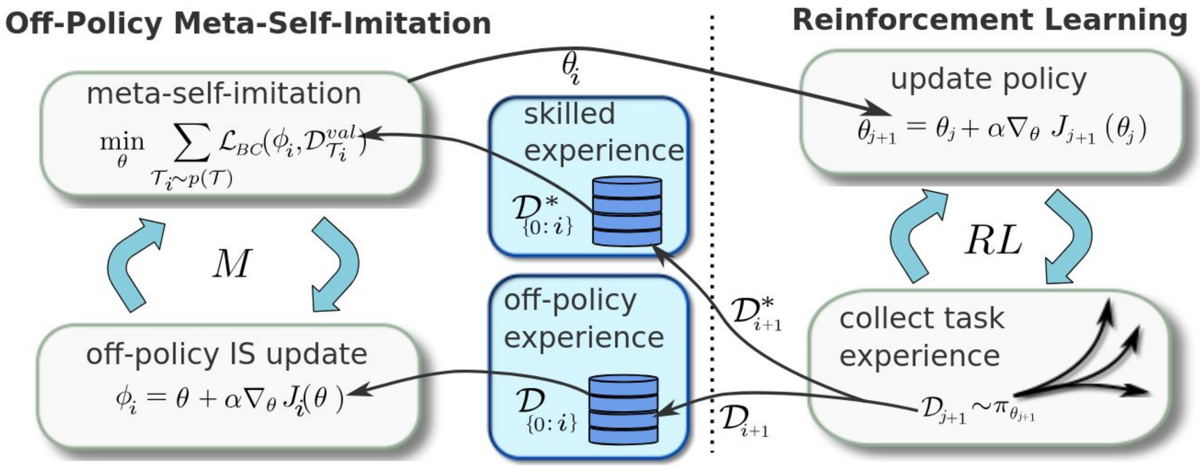




Javed, Khurram; White, Martha. (2019). Meta Learning Representations for Continual Learning

Catastrophic Forgetting: An Idea

Use representative task trajectory.



Berseth et al. (2019) Continual Meta Policy Search.

Rough Plans for Future Work

- Investigate plasticity of meta-gradients / viability for continual learning.
- Improving stability of online meta RL.
- Mitigating interference / improving transfer in continual reinforcement learning.
- How to co-learn tasks and successor features for structured representation in CRL.

If any of this sounds interesting reach out!