Meta Learning the Step Size in Policy Gradient Methods

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Outline

1 Reinforcement Learning

2 Meta Learning

Background Knowledge & State of the Art

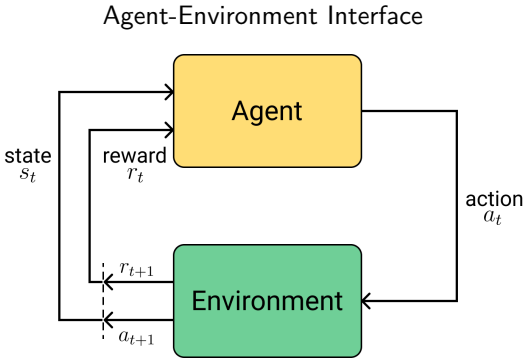
3 Proposed Solution

4 Experimental Results

5 Conclusions

Contributions & Open Questions

Sequential Decision Making Problems



Markov Decision Process:

- **MDP**: $\mathcal{M} = \langle \mathcal{S}, \mathcal{A}, P, R, \gamma, \mu \rangle$
- **Return**: $G_{t_0} = \sum_{t=t_0}^{T} \gamma^{t-t_0} R(s_t, a_t)$
- **Parametric Policy**: $a \sim \pi_{\boldsymbol{\theta}}(\cdot \mid s)$
- **Action-Value Function**: $Q_\pi(s, a) = \mathop{\mathbb{E}}_{P,\pi} [G_0 \mid s_0 = s, a_0 = a]$
- **Goal**: $\arg\max_{\boldsymbol{\theta}} J_{\pi_{\boldsymbol{\theta}}} = \mathop{\mathbb{E}}_{P,\pi_{\boldsymbol{\theta}}} [G_0]$

Policy Gradient Methods

Policy Gradients (PG) main concepts:

- **Goal**: optimize policy $\pi_{\boldsymbol{\theta}}$ with a series of **Gradient Ascent** steps

Policy Gradient Update

$$\boldsymbol{\theta}_{t+1} = \boldsymbol{\theta}_t + \boldsymbol{\alpha} \nabla J(\boldsymbol{\theta}_t)$$

$$\nabla J(\boldsymbol{\theta}) = \sum_{s \in \mathcal{S}} \mu(s) \sum_{a \in \mathcal{A}} Q_\pi(s,a) \nabla \pi_{\boldsymbol{\theta}}(a \mid s) \qquad \text{(PGT)}$$

- **Hyperparameter**: step size $\boldsymbol{\alpha}$, regulates the magnitude of the update

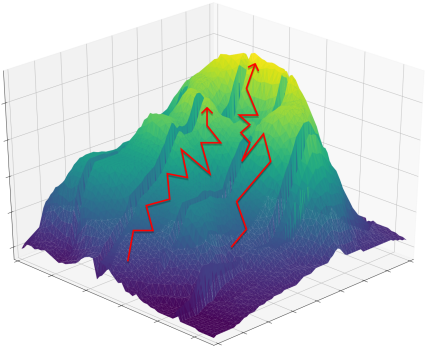
PG Methods - Drawbacks and Proposed Solution

Drawbacks:

- slow or **unstable convergence**
- high **sample inefficiency**
- manual **hyperparameters tuning**

Solution: learn a **Dynamic Step Size**

- maximize **learning speed**
- minimize **instability**



PG Gradient Ascent Example

Value Based Methods - Fitted Q Iteration

Main concepts:

- **Value-Based** methods: learn the optimal value function Q^*
- **Fitted Q Iteration** (FQI): approximate the Q function with a series of regressions

Main steps of FQI (Ernst et al., 2005):

1. Input set $\mathcal{F} = \{(s_i, a_i, s'_i, r_i)\}$
2. Build $\mathcal{TS} = \left\{\left(i^l, o^l\right)\right\}_l$, where: $i^l = \left(s_t^l, a_t^l\right)$ and $o^l = \hat{Q}_{n-1}\left(s_t^l, a_t^l\right)$
3. Use a **regression algorithm** to induce the function $\hat{Q}_n(\mathcal{S}, \mathcal{A})$

repeat

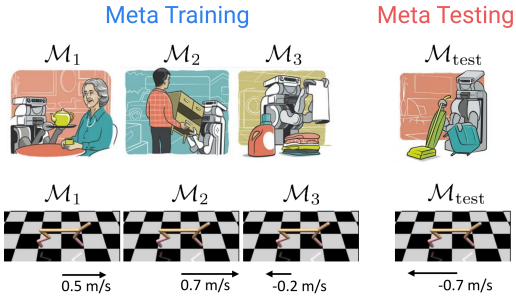
Meta Learning - Learning How to Learn

Main Goals:

- **learn quickly**, using few training samples
- **adapt to changes** and dynamic scenarios

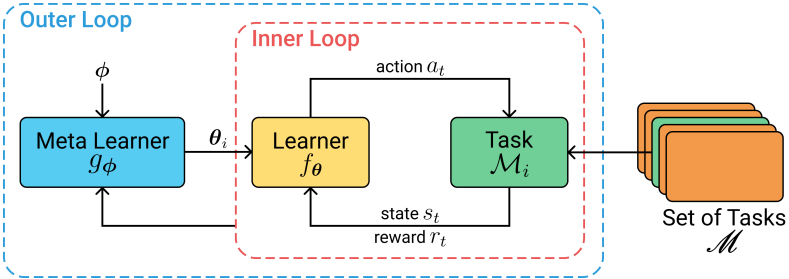
Meta Learning works **above Machine Learning**:

- the training samples are **learning instances**



Examples of Meta Learning Tasks in RL

Meta Reinforcement Learning

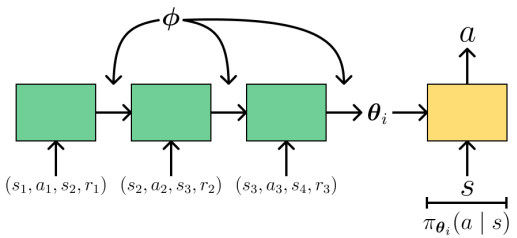


Meta-RL Two Levels Architecture

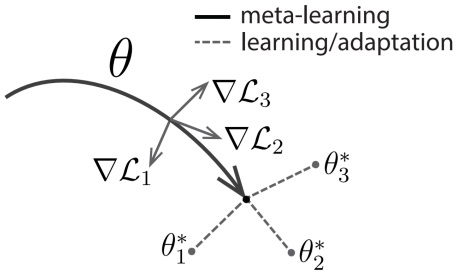
General Meta Reinforcement Learning (Meta-RL) training process:

1. Sample a **random MDP** $\mathcal{M}_i \sim \mathscr{M}$
2. Reset the hidden state of the **learner** f_θ
3. Optimize the model to the task $\mathcal{M}_i$ according to the **meta learner** g_ϕ

Meta-RL State of the Art



RL^2 (Duan et al., 2016),
Learning to RL (Wang et al., 2017)



MAML (Finn et al., 2017),
Reptile (Nichol et al., 2018)

Proposed Framework: Meta-MDP

Given a set of MDPs $\mathscr{M} = \{\mathcal{M}_\omega\}$, defined by a **context** $\omega \in \Omega$:

A **meta-MDP** is a tuple $\langle \mathcal{X}, \mathcal{H}, \mathcal{L}, \tilde{\gamma}, (\mathscr{M}, p), (\boldsymbol{\theta}, q), f \rangle$, where:

- $\mathcal{X}$ is the **meta state space**
- $\mathcal{H}$ is the **meta learning action**
- $\mathcal{L}$ is the **meta reward function**
- $f : \boldsymbol{\theta} \times \mathcal{H} \to \boldsymbol{\theta}$ is the update algorithm

Meta Reward Function Proposed:

$$\mathcal{L}(x, \boldsymbol{\theta}, h) := J_i(f(\boldsymbol{\theta}, h)) - J_i(\boldsymbol{\theta}) = \underbrace{J_i\left(\boldsymbol{\theta} + h \nabla_{\boldsymbol{\theta}} J_i(\boldsymbol{\theta})\right) - J_i(\boldsymbol{\theta})}_{\text{Gradient Ascent Case}}$$

Lipschitz Meta-MDP

Lipschitz Continuity (LC)

$$\forall x, x' \in X, d_Y\left(f(x), f\left(x'\right)\right) \leqslant L_f d_X\left(x, x'\right)$$

Given a set of LC tasks $\mathscr{M} = \{\mathcal{M}_\omega\}_{\omega \in \Omega}$:

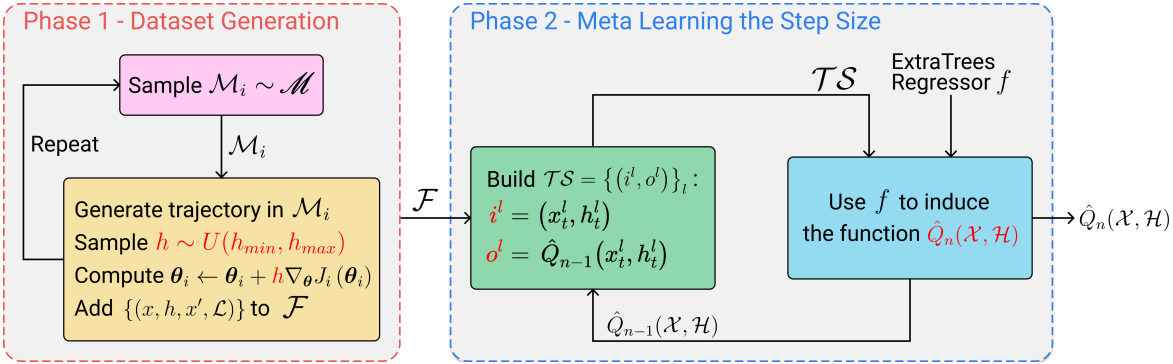
Bound in the Action-Value Function Q^π_ω

$$\left|Q^\pi_{\omega_1}(s,a) - Q^\pi_{\omega_2}(s,a)\right| \leqslant L_{\omega_Q}(\pi) d_\Omega(\omega_1, \omega_2),$$

where $L_{\omega_Q}(\pi) = \dfrac{L_{\omega_r} + \gamma L_{\omega_p} L_{V^\pi}(\omega)}{1-\gamma}$

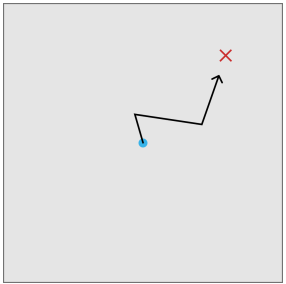
Similar guarantees have been derived for the gradient $\nabla J_\omega(\boldsymbol{\theta})$.

Proposed Algorithm: Learning the Step Size

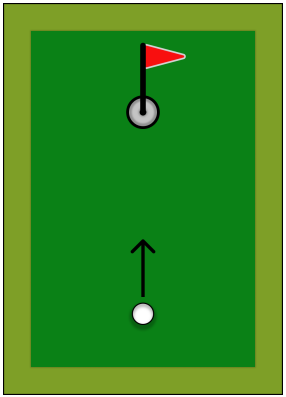


Meta Learning the Step Size with FQI:
Dataset Generation & Meta Training

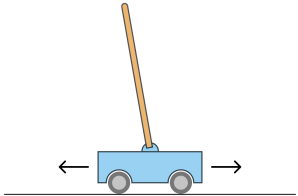
Experimental Settings



Navigation2D:
random goal point

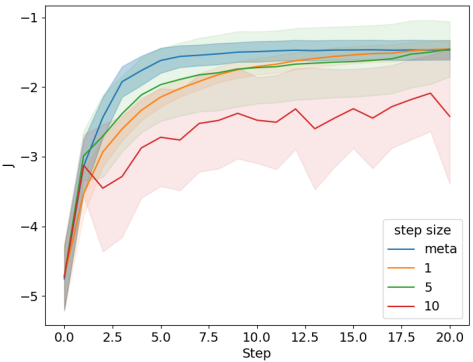


MiniGolf:
random putter length
and friction coefficient

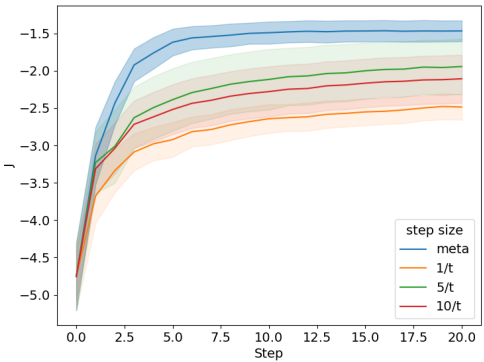


CartPole:
random gravity acceleration
and pole mass

Navigation2D - Dynamic Step Size vs Benchmarks

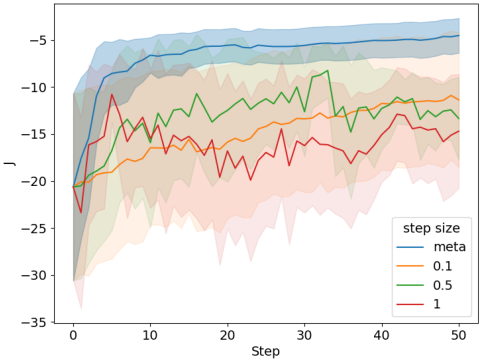


Nav2D - Expected Return J:
Dynamic Step Size vs Fixed Step Size α

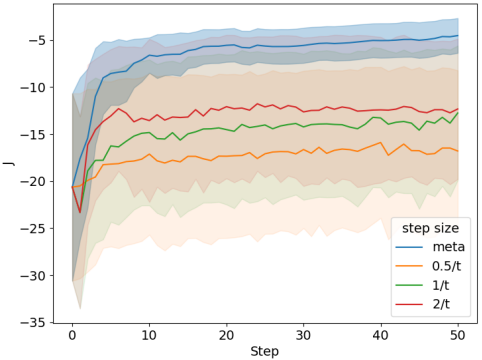


Nav2D - Expected Return J:
Dynamic Step Size vs Decreasing Step Size $\frac{\alpha}{t}$

MiniGolf - Dynamic Step Size vs Benchmarks

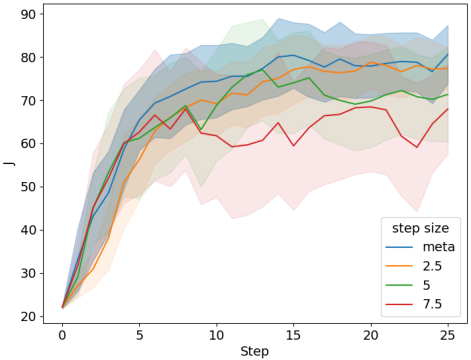


MiniGolf - Expected Return J:
Dynamic Step Size vs Fixed Step Size α

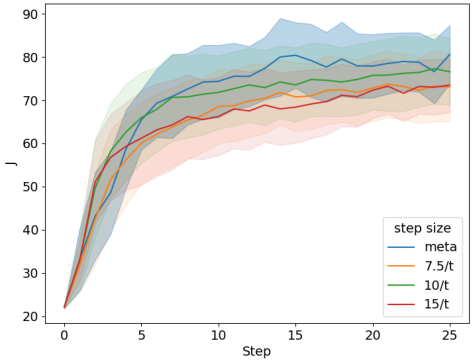


MiniGolf - Expected Return J:
Dynamic Step Size vs Decreasing Step Size $\frac{\alpha}{t}$

CartPole - Dynamic Step Size vs Benchmarks



CartPole - Expected Return J:
Dynamic Step Size vs Fixed Step Size α



CartPole - Expected Return J:
Dynamic Step Size vs Decreasing Step Size $\frac{\alpha}{t}$

Conclusions

Results achieved:

1. **Meta-MDP**: introduced new framework to represent meta-RL tasks;
2. **LC meta-MDP**: derived guarantees on the performance under the LC property;
3. **Dynamic Step Size**: proposed algorithm to learn a dynamic step size in meta-MDPs with PG learners;
4. **Experiments**: evaluated performance in different simulated settings.

Thank You for Your Attention

References

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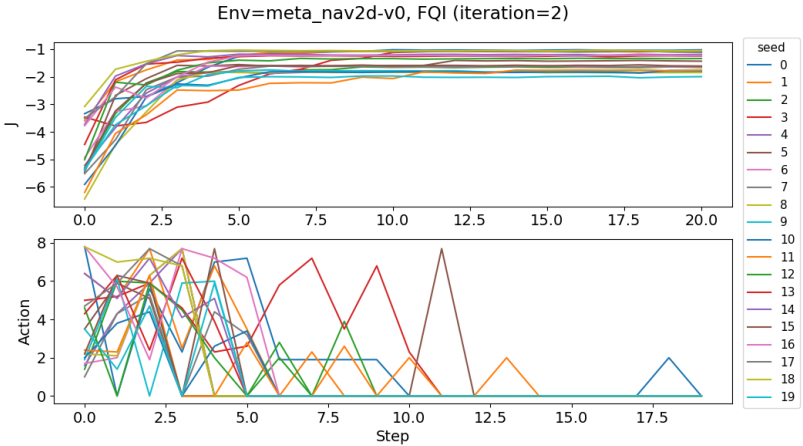
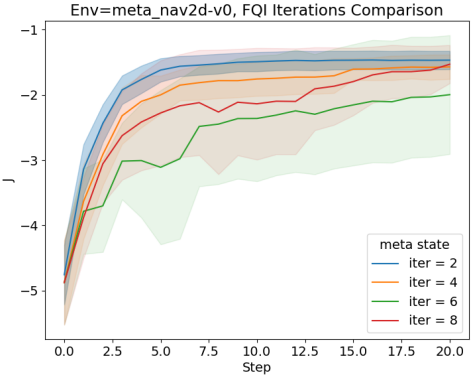
Navigation2D Details

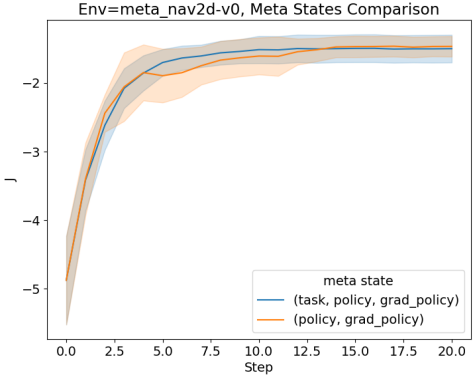


Dynamic PG - Expected return J and step size α at each meta step

Navigation2D Details

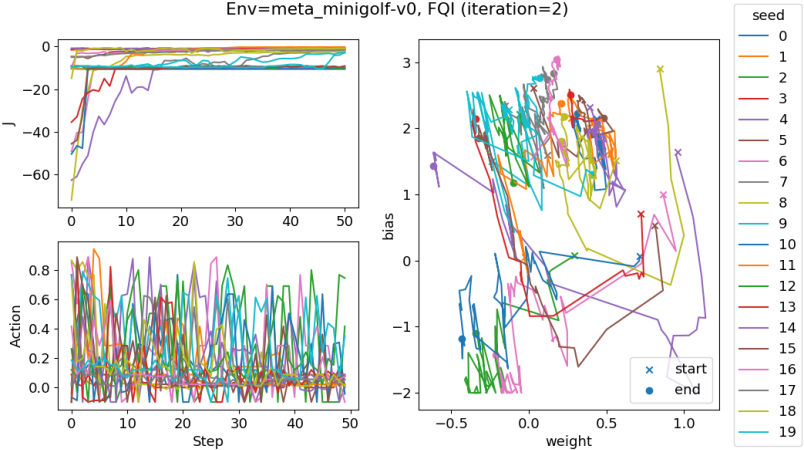


Performance of different iterations of the FQI algorithm



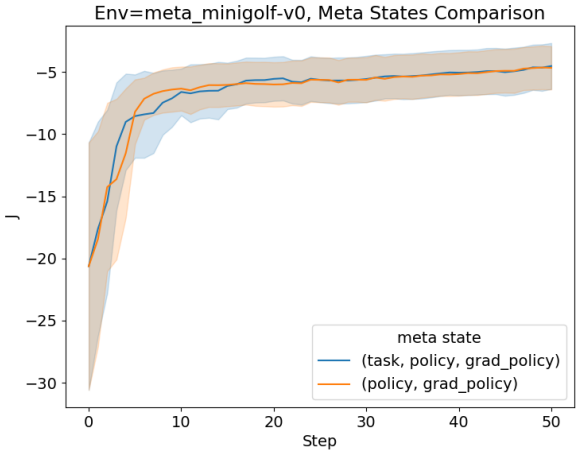
Performance of two meta states:
$x_1 = \langle \boldsymbol{\theta}_t, \nabla_{\boldsymbol{\theta}} J_i(\boldsymbol{\theta}_t), \phi_{\mathcal{M}}(\mathcal{M}_t) \rangle$,
$x_2 = \langle \boldsymbol{\theta}_t, \nabla_{\boldsymbol{\theta}} J_i(\boldsymbol{\theta}_t) \rangle$

MiniGolf Details



Dynamic PG - Expected return J, step size α and policy parameters $\boldsymbol{\theta}$ at each meta step

MiniGolf Details



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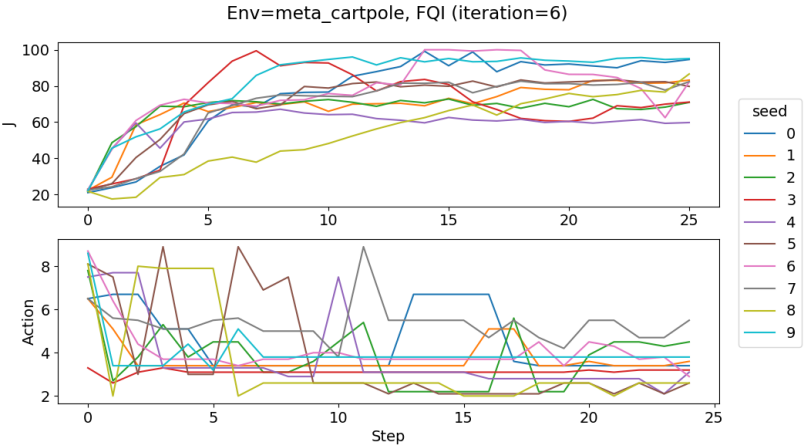
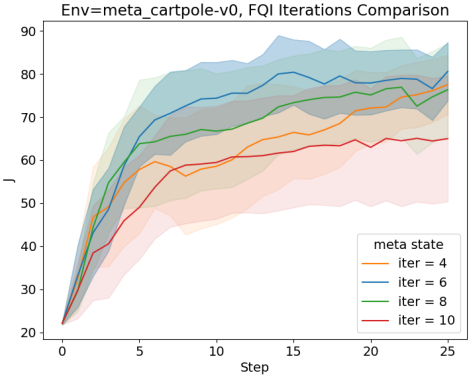


Dynamic PG - Expected return J and step size α at each meta step

CartPole Details



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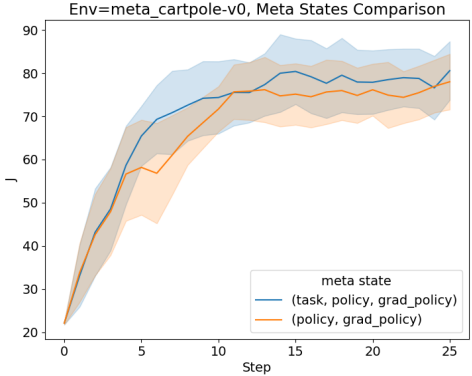

Performance of two meta states:
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