General Policy Evaluation and Improvement by Learning to Identify Few But Crucial States

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Problem and Motivation

- **Reinforcement Learning (RL):** Find optimal policy π^*
- **Policy optimization:** Given a class of policies, find the policy parameters maximizing $J(\pi_{\boldsymbol\theta})$ (Sutton et al., 1999):

$$J(\pi_{\boldsymbol\theta}) = \int_{\mathcal{S}} \mu_0(s) V^{\pi_{\boldsymbol\theta}}(s)\,\mathrm{d}s = \int_{\mathcal{S}} \mu_0(s) \int_{\mathcal{A}} \pi_{\boldsymbol\theta}(a|s) Q^{\pi_{\boldsymbol\theta}}(s,a)\,\mathrm{d}a\,\mathrm{d}s$$

- **Problem:** Value functions are defined for a *single policy*. During optimization, the information on previous policies is potentially lost
- **Solution idea:** Learn a single value function able to evaluate many policies

Parameter-Based Value Functions

- **Parameter-Based Value Functions** (Faccio et al., 2021) generalize over multiple policies by incorporating the policy parameters as an additional input
- **PSVF**: Parameter based state-value function

$$V(s, \boldsymbol\theta) := \mathbb{E}[R_t | s_t = s, \boldsymbol\theta]$$

- **PAVF**: Parameter based action-value function

$$Q(s, a, \boldsymbol\theta) := \mathbb{E}[R_t | s_t = s, a_t = a, \boldsymbol\theta]$$

- **PSSVF**: Parameter based start-state-value function

$$V(\boldsymbol\theta) := \mathbb{E}[R_0 | \boldsymbol\theta]$$

- The PSSVF models $J(\theta)$ directly as a differentiable function $V(\theta)$, which is the expectation of $V(s,\theta)$ over the initial states

$$V(\theta) := \mathbb{E}_{s\sim\mu_0(s)}[V(s,\theta)] = \int_{\mathcal{S}} \mu_0(s) V(s,\theta)\,\mathrm{d}s = J(\pi_\theta).$$

If we can learn $V_w(\theta)$, we can improve the policy by simply taking gradient ascent steps

$$\nabla_{\boldsymbol\theta} J(\pi_{\boldsymbol\theta}) = \nabla_{\boldsymbol\theta} V_w(\pi_{\boldsymbol\theta})$$

- **Problem:** How can we give the policy parameters as input to the value function when π_θ is a neural network?

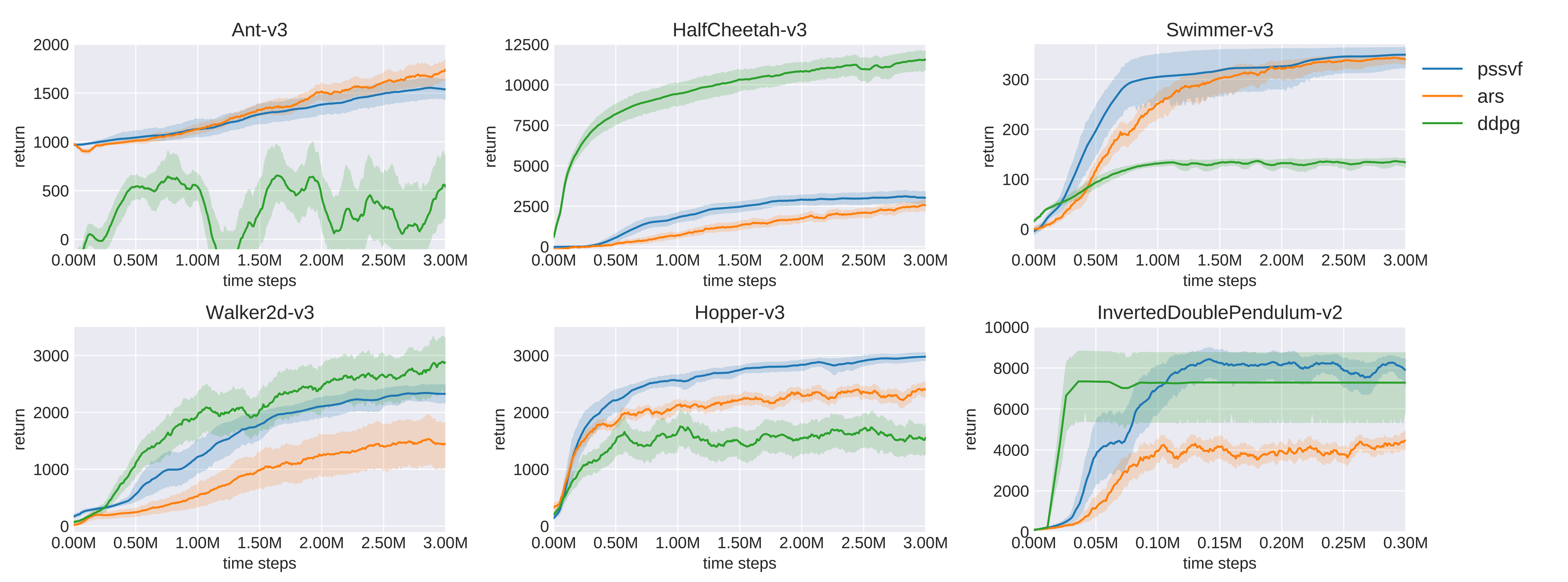
Policy fingerprinting

- **Policy fingerprinting** (Harb et al., 2020) creates a lower-dimensional policy representation
- It learns a set of K **probing states** $\{\tilde{s}_k\}_{k=1}^K$ and an evaluation function V_ϕ
- To evaluate a policy π_θ, it computes the 'probing actions' $\tilde{a}_k$ that the policy produces in the probing states. Then the concatenated vector of these actions is given as input to V_ϕ and mapped to the return
- Setting $w = \{\phi, \tilde{s}_1, \dots \tilde{s}_K\}$, we optimize V_w minimizing MSE:

$$\min_w \mathcal{L}_V := \min_w \mathop{\mathbb{E}}_{(\pi_\theta, r)\in B}[(V_w(\theta) - r)^2]$$
$$= \min_{\phi, \tilde{s}_1, \dots \tilde{s}_K} \mathop{\mathbb{E}}_{(\pi_\theta, r)\in B}[(V_\phi([\pi_\theta(\tilde{s}_1), \dots, \pi_\theta(\tilde{s}_K)]) - r)^2]$$

Main results

- Comparison with DDPG (Lillicrap et al., 2015) and ARS (Mania et al., 2018) using deep deterministic policies (2 hidden layers, 256 neurons per layer)



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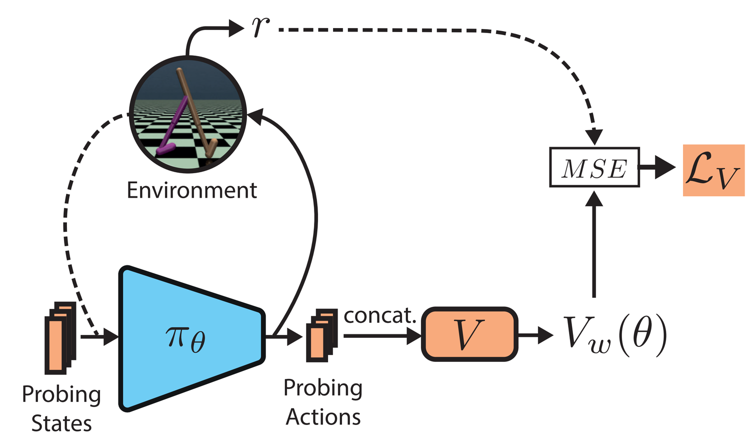
Actor Critic Algorithm



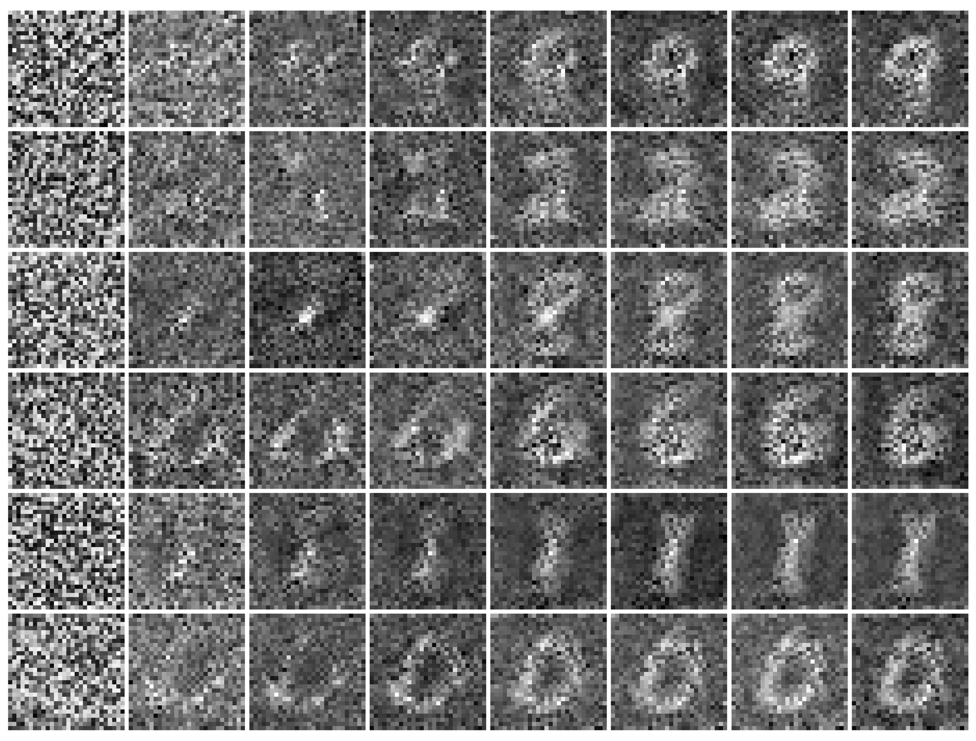
Off-policy actor-critic with PSSVF

Given the behavioral π_b, find $\pi_{\boldsymbol\theta}$ **maximizing** $J(\boldsymbol\theta)$:

1. Collect data with π_b (expensive in RL)
2. Use data to train $V(\boldsymbol\theta)$
3. Improve $\pi_{\boldsymbol\theta}$ following $\nabla_{\boldsymbol\theta} J(\pi_{\boldsymbol\theta})$ (offline optimization)
4. Set new behavioral $\pi_{\boldsymbol\theta} \leftarrow \pi_b$
5. Repeat until convergence

Demonstration on MNIST

- We apply our algorithm to MNIST classification. The return is the negative supervised loss. We obtain 87% accuracy. Learned probing states are digits

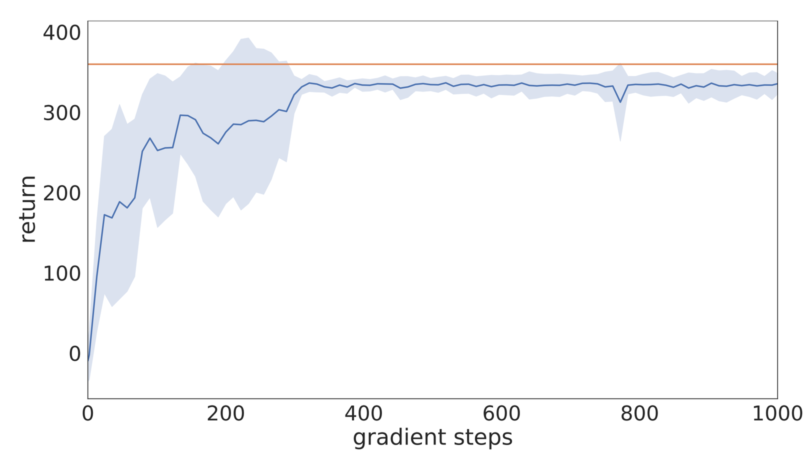


Offline policy improvement:

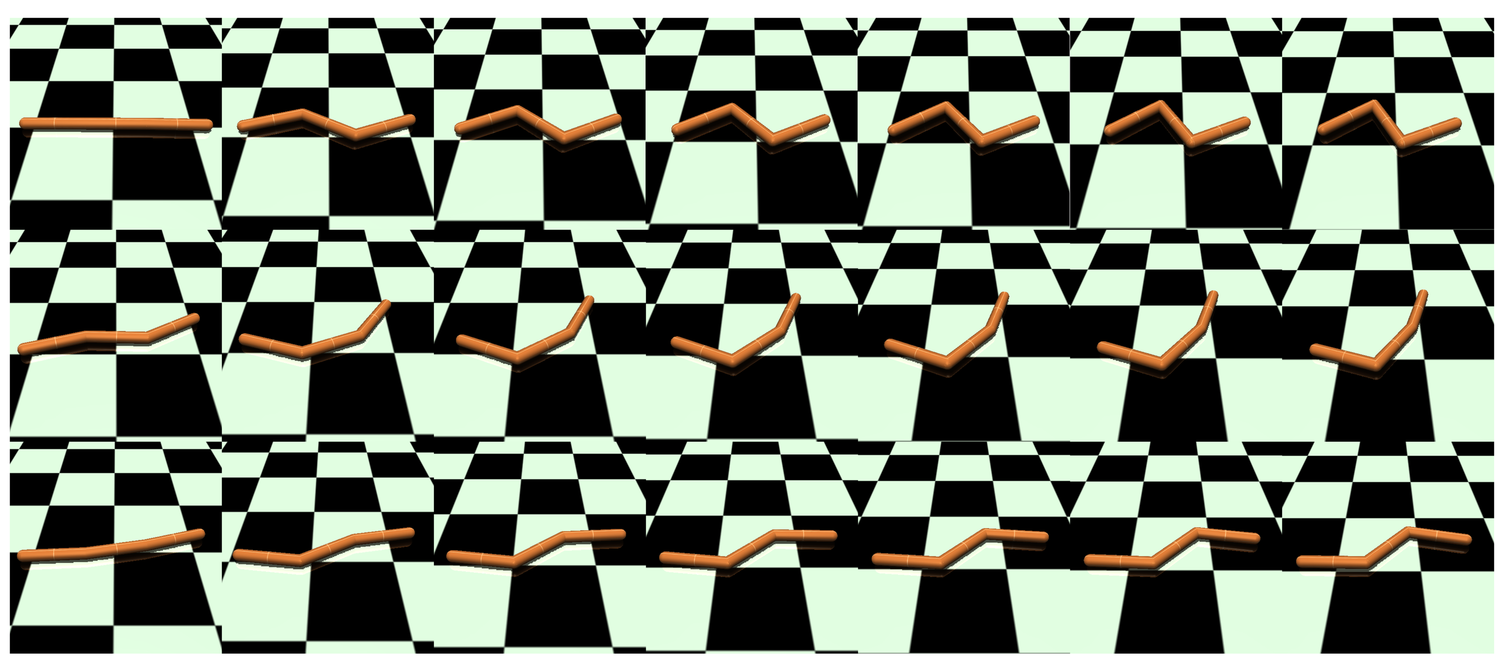
- With an offline dataset $\{\pi_{\theta_i}, l_i\}_{i=1}^N$ of randomly initialized CNNs and their losses (maximum accuracy 12%), we train V_w to evaluate such policies
- We randomly initialize a new CNN and take many steps of gradient ascent through the fixed value function, obtaining a final CNN whose accuracy is around 65% on the test set

More Results

- A PSSVF trained using deep deterministic policies zero-shot learns a linear policy with similar performance in Swimmer



- The method extracts crucial abstract knowledge about the environment in form of very few learned abstract states sufficient to fully specify the behavior of many policies
- A randomly initialized policy can learn optimal behaviors in Swimmer by knowing how to act only in the following 3 crucial learned states (similar results for Hopper with 5 states):



- Videos of learned probing states for the RL experiments: