Generalization in Deep Reinforcement Learning

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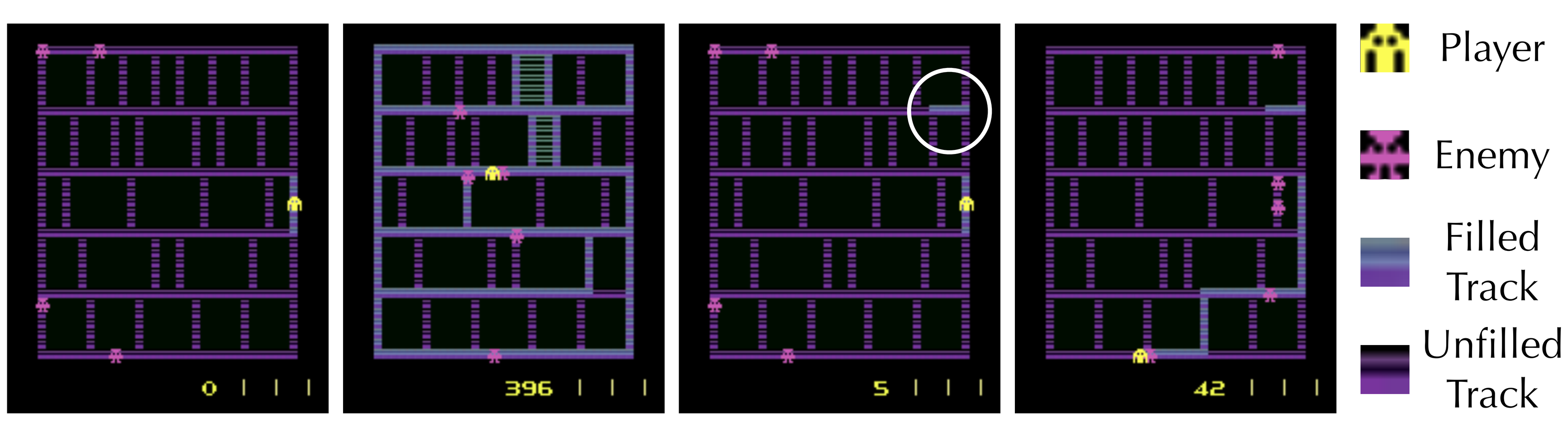
1. Motivation

Deep reinforcement learning (RL) agents can perform complex tasks using only pixel-level visual input data. Given the apparent competence of some of these agents, it is tempting to see them as possessing a general understanding of their environments.

To what extent do the accomplishments of deep RL agents demonstrate generalization, and how can we recognize such a capability when presented with only a black-box controller?



Default start | Default death | Modified start (FLS) | Modified death

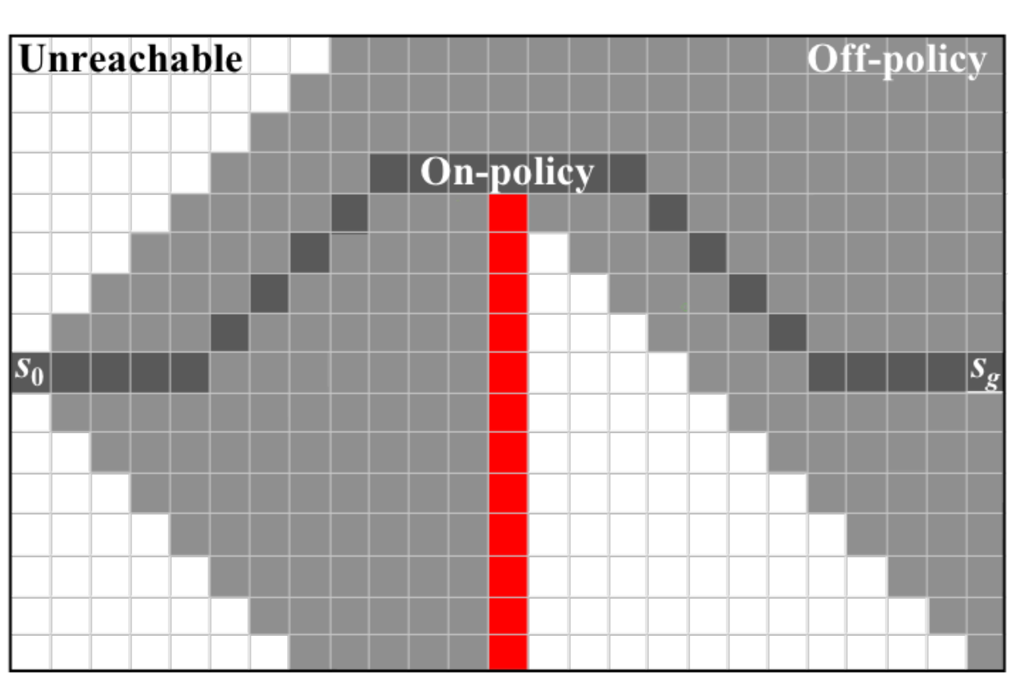
An agent trained to play the Atari game of Amidar using the state-of-the-art dueling network architecture [3,4,5] achieves large rewards when evaluated from the default initial state, but small **non-adversarial** modifications dramatically degrade performance.

2. Recasting Generalization

Naïve evaluation of a policy on held-out training states only measures an agent's ability to *use* data after it is collected. Using this method, we could incorrectly claim that an agent has generalized, even if it only performs well on a small subset of states.

We partition the universe of possible input states into three sets, according to how the agent can encounter them following its learned policy π from $s_0 \in S_0$, the set of initial states.

- On-policy states, S_{on}, can be encountered by following π from some s_0.
- Off-policy states, S_{off} can be encountered by following any $\pi' \in \Pi$, the set of all policy functions.
- Unreachable states, $S_{unreachable}$ can not be encountered by following any $\pi' \in \Pi$, but are still in the domain of the state transition function $T(s, a, s')$.



In this gridworld example, the agent can take actions *up-right, right,* and *down-right*.

We define a q-value based agent's generalization abilities via the following, where δ and β are small positive values. $v^*(s)$ is the optimal state-value, $v_\pi(s)$ is the actual state-value by following π, and $\hat{v}(s)$ is the estimated state-value. $q^*(s, a)$, $q_\pi(s, a)$, and $\hat{q}(s, a)$, are the corresponding state-action values.

Definition 1 (Repetition) *An RL agent has high repetition performance, G_R, if $\delta > |\hat{v}(s) - v_\pi(s)|$ and $\beta > v^*(s) - v_\pi(s)$, $\forall s \in S_{on}$.*

Definition 2 (Interpolation) *An RL agent has high interpolation performance, G_I, if $\delta > |\hat{q}(s, a) - q_\pi(s, a)|$ and $\beta > q^*(s, a) - q_\pi(s, a)$, $\forall s \in S_{off}, a \in A$.*

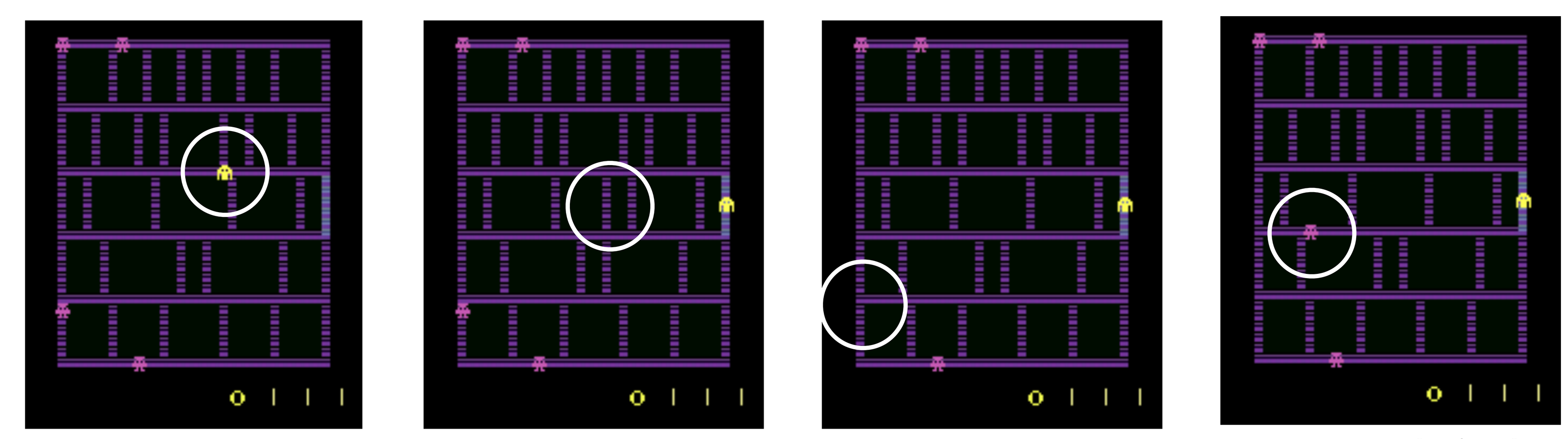
Definition 3 (Extrapolation) *An RL agent has high extrapolation generalization, G_E, if $\delta > |\hat{q}(s, a) - q_\pi(s, a)|$ and $\beta > q^*(s, a) - q_\pi(s, a)$, $\forall s \in S_{unreachable}, a \in A$.*

An agent interacting in the grid-world environment learns tabular q-values, therefore we should not expect it to satisfy any reasonable definition of generalization. Given enough exploration, $\hat{v}(s)$ would converge to $v^*(s)$ for all $s \in S_{off}$. Only the definition G_E is consistent with our intuition, that function-approximation is necessary to achieve generalization.

3. Empirical Methodology

Given a parameterized simulator we can intervene on individual components of latent state and forward-simulate an agent's trajectory through the environment using the simulator as the transition function of the MDP.

Intervening on individual components of latent state produces unreachable states, enabling empirical tests of an agent's generalization capabilities.



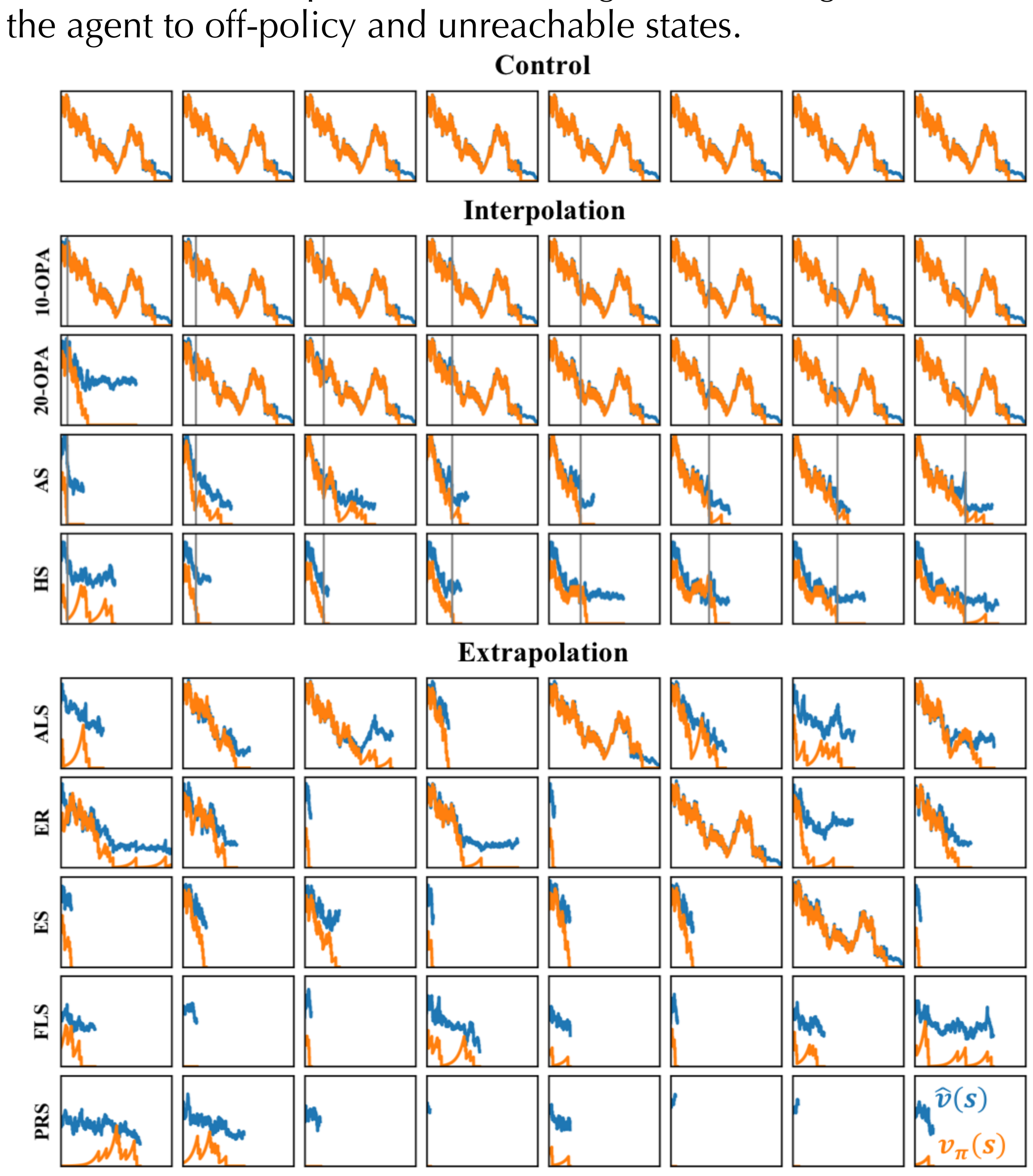
Player random start (PRS) | Added line segment (ALS) | Enemy removal (ER) | Enemy shifted (ES)

We can generate off-policy states by having the agent take k random actions during its trajectory (k-OPA) or extracting states from the trajectories of alternative agents (AS) and human players [1] (HS).

4. Analysis Case-Study

To demonstrate theses ideas we implement Intervenidar, a fully parameterized version of the Atari game of Amidar. Unlike previous work on adversarial attacks [1], interventions in Intervenidar change the latent state itself, not only the agent's perception of state.

We train the state-of-the-art dueling network architecture, double Q-loss function, and prioritized experience replay [3,4,5] using the standard pixel-based Atari MDP specification [2] with the default start position of the original Amidar game. After convergence, we expose the agent to off-policy and unreachable states.



While the agent's state-value estimates (blue) are consistent with the actual state-value (orange) in the control setting, this is not true when the agent is exposed to unreachable states. The agent consistently obtains dramatically less reward from such states.

4. Conclusions

- We propose a novel characterization of a black-box RL agent's generalization abilities based on performance from on-policy, off-policy, and unreachable states.
- We provide empirical methods for evaluating a RL agent's generalization abilities using intervenable parameterized simulators.
- We demonstrate these empirical methods using Intervenidar, a parameterized version of the Atari game of Amidar. We find that the state-of-the-art dueling DQN architecture fails to generalize to small changes in latent-state.

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