Lambda-Policy Iteration with Randomization for Contractive Models with Infinite Policies: Well-Posedness and Convergence*

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Abstract

Abstract dynamic programming (DP) models are used to analyze λ-policy iteration with randomization (λ-PIR) algorithms. Particularly, contractive models with infinite policies are considered and it is shown that well-posedness of the λ-operator plays a central role in the algorithm. In addition, we identify the conditions required to guarantee convergence with probability one when the policy space is infinite. Guided by the analysis, we exemplify a data-driven approximated implementation of the algorithm for estimation of optimal costs of constrained control problems, where promising numerical results are found.

Motivations

λ-PIR, proposed in [1], belongs to the broad class of policy iteration (PI) methods. In particular, it brings to bears the rich results for implementations due to its close connections to

- **TD(λ):** temporal difference (TD) learning ideas;
- **Proximal algorithm:** prominent methods in convex optimization [2];
- **Value iteration:** a principle method for DP.

However, no analysis is given for problems with infinite states and/or infinite policies.

Problems

- **Well-posedness:**

  Is the λ-PIR well-posed for problems with infinite states and policies?

- **Convergence:**

  Given the λ-PIR is well-posed, will it converge to the optimal in sought?

Preliminaries

Given state space X, control space U, and policy space $\mathcal{M} = \{\mu \,|\, \mu(x) \in U(x), \forall x \in X\}$, we study the mappings of the form $H : X \times U \times \mathcal{R}(X) \to \mathbb{R}$, and the ones

$$(T_\mu J)(x) = H(x, \mu(x), J),$$

$$(TJ)(x) = \inf_{\mu \in \mathcal{M}} (T_\mu J)(x).$$

Principle properties are:

- **Uniform contraction:**

  For some $\alpha \in (0,1)$, $\forall J, J' \in \mathcal{B}(X)$, $\mu \in \mathcal{M}$, it holds that

  $$\|T_\mu J - T_\mu J'\| \leq \alpha \|J - J'\|.$$

- **Monotonicity:**

  $\forall J, J' \in \mathcal{B}(X)$, it holds that $J \leq J'$ implies $\forall x \in X$, $u \in U(x)$,

  $$H(x, u, J) \leq H(x, u, J').$$

Main Results

The operator, named as λ-operator, is

$$(T_\mu^{(\lambda)} J)(x) = (1-\lambda) \sum_{\ell=1}^{\infty} \lambda^{\ell-1} (T_\mu^\ell J)(x). \quad (1)$$

Given $J_k \in \mathcal{B}(X)$ and $p_k \in (0,1)$, λ-PIR computes the policy μ^k and cost approximate J_{k+1} as

$$T_{\mu^k} J_k = TJ_k;\ J_{k+1} = \begin{cases} T_{\mu^k} J_k, & p_k, \\ T_{\mu^k}^{(\lambda)} J_k, & \text{o.w.} \end{cases} \quad (2)$$

1 Well-posedness

Theorem 1 *Let the set of mappings $T_\mu : \mathcal{B}(X) \to \mathcal{B}(X)$, $\mu \in \mathcal{M}$, satisfy the contraction property. Consider the mappings $T_\mu^{(w)}$ defined point-wise as*

$$(T_\mu^{(w)} J)(x) = \sum_{\ell=1}^{\infty} w_\ell(x) (T_\mu^\ell J)(x),\ x \in X, \quad (3)$$

with $w_\ell(x) \geq 0$ and $\sum_{\ell=1}^{\infty} w_\ell(x) = 1$. Then the range of $T_\mu^{(w)}$ is a subset of $\mathcal{B}(X)$, viz., $T_\mu^{(w)} : \mathcal{B}(X) \to \mathcal{B}(X)$; and $T_\mu^{(w)}$ is a contraction.

2 Convergence

Theorem 2 *Let relevant assumptions hold. Given $J_0 \in \mathcal{B}(X)$ such that $TJ_0 \leq J_0$, the sequence $\{J_k\}_{k=0}^{\infty}$ generated by algorithm (2) converges in norm to J^* with probability one.*

Corollary 2.1 *Let $H(\cdot,\cdot,\cdot)$ have the form*

$$H(x, u, J) = \int_X \big(g(x, u, y) + \alpha J(y)\big) d\mathbb{P}(y|x, u) \quad (4)$$

where $g : X \times U \times X \to \mathbb{R}$, $\alpha \in (0,1)$ and $\mathbb{P}(\cdot|x,u)$ is the probability measure conditioned on (x,u) for certain MDP. Let $v(x) = 1\ \forall x \in X$, and relevant assumptions hold. Given arbitrary $J_0 \in \mathcal{B}(X)$, the sequence $\{J_k\}_{k=0}^{\infty}$ generated by algorithm (2) converges in norm to J^* with probability one.

Numerical Example

Consider a torsional pendulum system:

$$\dot{\phi} = \omega,\ \dot{\omega} = M^{-1}(-mgl \sin\phi - \gamma\omega + \tau),$$

with constrained state and control spaces. It is discretized to obtain a constrained optimal control problem.

- The closed loop system behavior greatly improved after training, see Fig. 1.

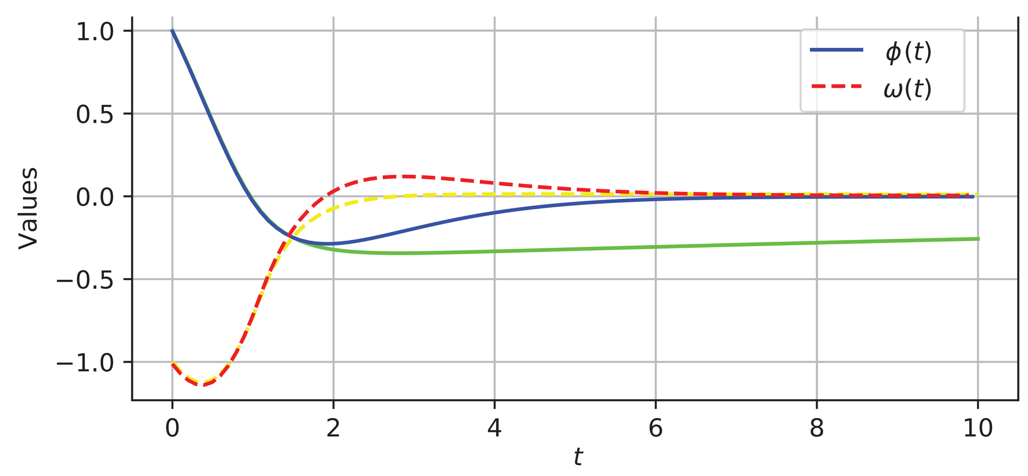

Figure 1: Closed loop system trajectory before (yellow and green) and after training (red and blue).

- The cost function converges after 5 iterations, see Figs. 2 and 3 for plots along the axes where $\omega = 0$ and $\phi = 0$.

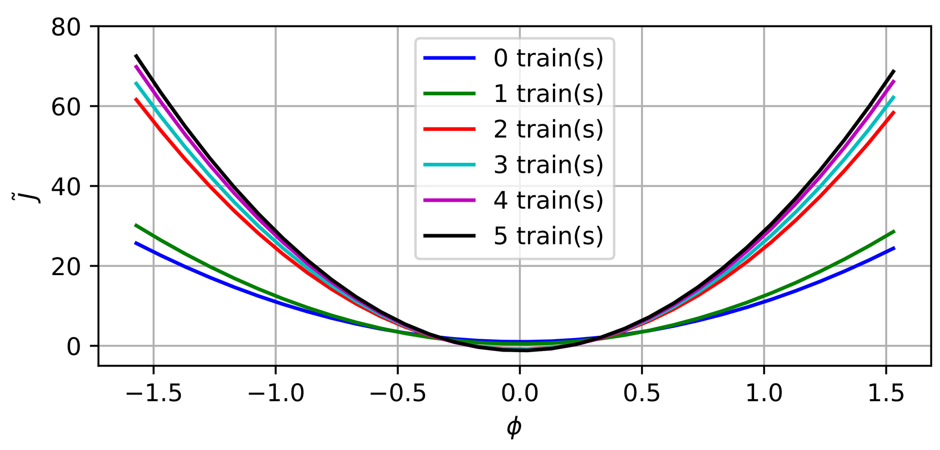

Figure 2: Cost function along the axis $\omega = 0$ after different training iterations.

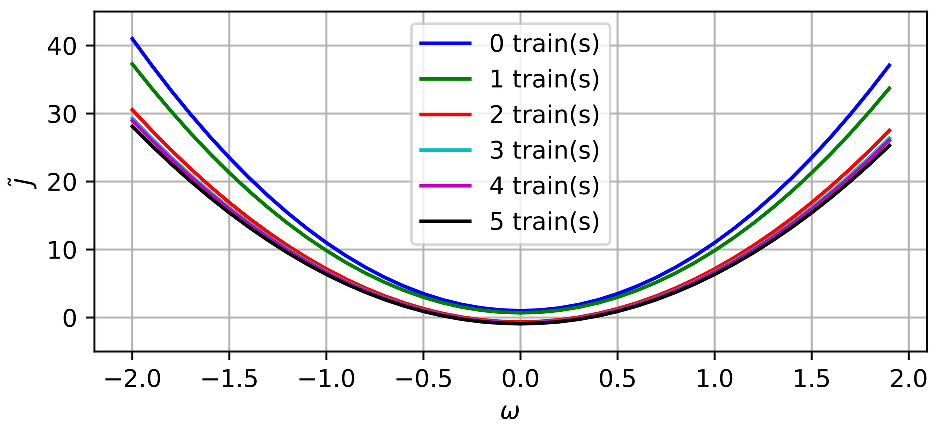

Figure 3: Cost function along the axis $\phi = 0$ after different training iterations.

- Compared with approximate VI and and optimistic PI (OPI) [3], λ-PIR shows faster convergence against VI; and requires fewer samples when compared with OPI, see Figs. 4 and 5.

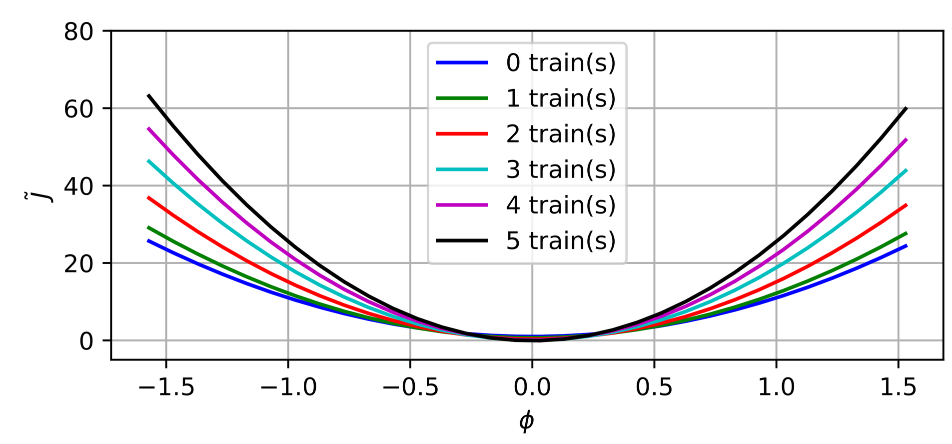

Figure 4: Cost functions of VI along the axis $\omega = 0$.

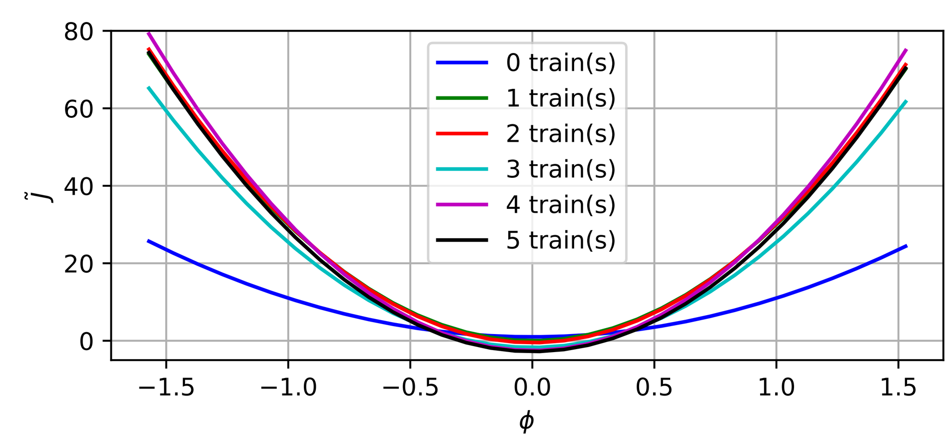

Figure 5: Cost functions of OPI along the axis $\omega = 0$.

References

[1] D. P. Bertsekas. *Abstract dynamic programming*. Athena Scientific, 2nd edition, 2018.

[2] D. P. Bertsekas. Proximal algorithms and temporal difference methods for solving fixed point problems. *Computational Optimization and Applications*, 70(3):709–736, 2018.

[3] B. Scherrer, *et al.* Approximate modified policy iteration and its application to the game of Tetris. *Journal of Machine Learning Research*, 16:1629–1676, 2015.