

Performance Loss Bounds for Approximate Value Iteration with State Aggregation

Mathematics of Operations Research

Van Roy

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Problem Definition

- ▶ What is this paper about?
How to approximate J^* , the optimal cost-to-go function (value function), with Φr ?
 - ▶ State Aggregation
 - ▶ Value Iteration
 - ▶ In particular, how to find $r \in \mathbb{R}^K$?
- ▶ What is this paper NOT about?
How to partition the space (or find $\Phi \in \mathbb{R}^{|\varphi| \times K}$)?

⁰ $|\varphi|$ is the number of states

Approximating J



$$\min_r \|J - \Phi r\|_{2,\pi} \quad (1)$$

- ▶ Projection with respect to a weighted Euclidean norm $\|\cdot\|_\pi$

$$\|J\|_{2,\pi} = \left(\sum_{x \in \varphi} \pi(x) J^2(x) \right)^{1/2}$$

$\pi \in \mathbb{R}_+^{|\varphi|}$ is a vector of weights, showing the *importance* of each state

- ▶ To get r , we need to run value iteration

$$\Phi r^{(l+1)} = \Pi_\pi T \Phi r^{(l)}$$

Calculating r

$$\Phi r^{(l+1)} = \Pi_{\pi} T \Phi r^{(l)}$$

- ▶ T is the dynamic programming operator
- ▶ T is a contraction
- ▶ Π_{π} is max-norm nonexpansive
- ▶ Π_{π} operator (matrix) projects onto the column space of Φ with respect to a weighted Euclidean Norm that minimizes equation (1)



$$\Pi_{\pi} = \Phi(\Phi^T D \Phi)^{-1} \Phi^T D$$

where $D = \text{diag}(\pi_i)$

Bounds

- ▶ **Without considering** the importance weights, and when μ is greedy with respect to \tilde{J} we have the bound¹:

$$\|J_\mu - J^*\|_\infty \leq \frac{2\alpha}{1-\alpha} \|J^* - \tilde{J}\|_\infty \quad (2)$$

- ▶ **Considering** the importance weights and when $\Phi\tilde{r} = \Pi_\pi T\Phi\tilde{r}$
 - ▶ *Approximation Error Bound*

$$\|\Phi\tilde{r} - J^*\|_\infty \leq \frac{2}{1-\alpha} \min_{r \in \mathcal{R}^K} \|J^* - \tilde{J}\|_\infty$$

- ▶ *Performance Loss Bound*

$$(1-\alpha) \|J_{\mu\tilde{r}} - J^*\|_\infty \leq \frac{4\alpha}{1-\alpha} \min_{r \in \mathcal{R}^K} \|J^* - \Phi r\|_\infty$$

- ▶ **HOWEVER!!!**

¹ $\|J_\mu - J^*\|_\infty$ is performance loss

Using the Invariant Distribution

- ▶ if $\pi_{\tilde{r}}$ is the invariant state distribution of transition matrix $P_{\mu\tilde{r}}$ ²

$$(1 - \alpha)\pi_{\tilde{r}}^T(J_{\mu\tilde{r}} - J^*) \leq 2\alpha \min_{r \in \mathcal{R}^K} \|J^* - \Phi r\|_\infty$$

- ▶ Compare it with:

$$(1 - \alpha)\|J_{\mu\tilde{r}} - J^*\|_\infty \leq \frac{4\alpha}{1 - \alpha} \min_{r \in \mathcal{R}^K} \|J^* - \Phi r\|_\infty$$

- ▶ Weighting Euclidean Norm projection by the invariant distribution of a greedy (or ϵ -greedy) policy improves the performance loss.

² π is an invariant of P if $\pi^T P = \pi^T$

Thank You!