

## A APPENDIX

### A.1 PROOF OF THEOREM [1](#)

We initiate our discussion by introducing the performance disparity between the offline dataset and reality (represented by the universal uncertainty set) in Lemma [1](#). This serves as a foundation for the subsequent proof presented in Theorem [1](#).

**Lemma [1](#).** *[Reality Gap: Performance Gap between Offline Dataset and Reality(the universal uncertainty set)] The value of any policy  $\pi$  learned from  $P_B$  on the universal uncertainty set  $\mathcal{U}$  and the induced offline dataset transition kernel  $P_B$  satisfies:*

$$J_{\rho_0^B}(\pi, P_B) \geq \mathbb{E}_{P_0 \sim \mathcal{U}}(J_{\rho_0}(\pi, P_0)) - \frac{2R_{\max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[D_{TV}(\rho_0, \rho_0^B)] - \frac{2\gamma R_{\max}}{(1-\gamma)^2} \beta - \frac{2R_{\max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[\gamma^{T_{\mathcal{V}}^{\pi}}] \quad (11)$$

$$J_{\rho_0^B}(\pi, P_B) \leq \mathbb{E}_{P_0 \sim \mathcal{U}}(J_{\rho_0}(\pi, P_0)) + \frac{2R_{\max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[D_{TV}(\rho_0, \rho_0^B)] + \frac{2\gamma R_{\max}}{(1-\gamma)^2} \beta + \frac{2R_{\max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[\gamma^{T_{\mathcal{V}}^{\pi}}], \quad (12)$$

where  $\mathcal{V}$  is an unknown state action set defined as:  $(s, a) \in \mathcal{V}$  iff  $(s, a)$  is not in the offline dataset and  $T_{\mathcal{V}}^{\pi}$  denotes the hitting time of unknown states.

*Proof.* The inequalities provide a comparison of a policy  $\pi$ 's performance under two distinct dynamics models:  $P_B$  and  $P_0 \sim \mathcal{U}$ . To further understand these differences, it's beneficial to categorize the states into two groups: those present in the dataset (known state-actions) and those absent from it (unknown state-actions).

For state-action pairs present in the dataset, the primary objective is to concurrently couple the trajectory of any chosen policy on both the offline dataset MDP,  $M_B$ , and the reality MDP,  $M$ . Given an initial successful coupling, we consider the following constraint

$$\mathbb{E}_{P_0 \sim \mathcal{U}}[\|P_B(s, a) - P_0(s, a)\|_1] \leq \beta.$$

One can verify that this coupling can be consistently maintained in subsequent steps with a probability of  $1 - \beta$ . The likelihood of decoupling at time  $t$  is at most  $1 - (1 - \beta)^t$ .

For state-action pairs not present in the dataset, the divergence peaks: within  $M$ , the return upper bound for cumulative rewards post this encounter is  $\frac{R_{\max}}{1-\gamma}$ , whereas in  $M_B$ , the corresponding return lower bound is  $-\frac{R_{\max}}{1-\gamma}$ . This divergence can be quantified using the discount factor  $\mathbb{E}[\gamma^{T_{\mathcal{V}}^{\pi}}]$ , resulting in a measure of disparity introduced by these unidentified state-action pairs:  $\frac{2R_{\max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[\gamma^{T_{\mathcal{V}}^{\pi}}]$ .

So the total difference in the values of the policy  $\pi$  on the two MDPs can be upper bounded as:

$$|J_{\rho_0^B}(\pi, P_B) - \mathbb{E}_{P_0 \sim \mathcal{U}}[J_{\rho_0}(\pi, P_0)]| \quad (13)$$

$$\leq \frac{2R_{\max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[D_{TV}(\rho_0, \rho_0^B)] + \sum_t \gamma^t (1 - (1 - \beta)^t) \cdot 2 \cdot R_{\max} + \frac{2R_{\max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[\gamma^{T_{\mathcal{V}}^{\pi}}] \quad (14)$$

$$\leq \frac{2R_{\max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[D_{TV}(\rho_0, \rho_0^B)] + \frac{2R_{\max}\gamma\beta}{(1-\gamma)(1-\gamma \cdot (1-\beta))} + \frac{2R_{\max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[\gamma^{T_{\mathcal{V}}^{\pi}}] \quad (15)$$

$$\leq \frac{2R_{\max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[D_{TV}(\rho_0, \rho_0^B)] + \frac{2R_{\max}\gamma}{(1-\gamma)^2} \beta + \frac{2R_{\max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[\gamma^{T_{\mathcal{V}}^{\pi}}] \quad (16)$$

□

For ease of exposition, we restate Theorem [1](#) as follows.

**Theorem 11.** For any  $\epsilon_\pi$  sub-optimal policy, we have:

$$\begin{aligned} \mathbb{E}_{P_0 \sim \mathcal{U}}[J_{\rho_0}(\pi^*, P_0)] - \mathbb{E}_{P_0 \sim \mathcal{U}}[J_{\rho_0}(\pi, P_0)] &\leq \epsilon_\pi + \frac{4R_{\max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[D_{TV}(\rho_0, \rho_0^B)] + \frac{4\gamma R_{\max}}{(1-\gamma)^2} \beta \\ &\quad + \frac{2R_{\max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[\mathbb{E}[\gamma^{T_{\mathcal{V}}^\pi}]] + \frac{2R_{\max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[\mathbb{E}[\gamma^{T_{\mathcal{V}}^{\pi^*}}]]. \end{aligned} \quad (17)$$

*Proof.* By Lemma 11 we have

$$\begin{aligned} \mathbb{E}_{P_0 \sim \mathcal{U}}[J_{\rho_0}(\pi, P_0)] &\geq J_{\rho_0^B}(\pi, P_B) - \frac{2R_{\max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[D_{TV}(\rho_0, \rho_0^B)] - \frac{2R_{\max}\gamma}{(1-\gamma)^2} \beta - \frac{2R_{\max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[\mathbb{E}[\gamma^{T_{\mathcal{V}}^\pi}]] \\ &\geq J_{\rho_0^B}(\pi^*, P_B) - \epsilon_\pi \end{aligned} \quad (18)$$

$$- \frac{2R_{\max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[D_{TV}(\rho_0, \rho_0^B)] - \frac{2R_{\max}\gamma}{(1-\gamma)^2} \beta - \frac{2R_{\max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[\mathbb{E}[\gamma^{T_{\mathcal{V}}^\pi}]] \quad (19)$$

$$\geq \mathbb{E}_{P_0 \sim \mathcal{U}}[J_{\rho_0}(\pi^*, P_0)] - \epsilon_\pi \quad (20)$$

$$- \frac{4R_{\max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[D_{TV}(\rho_0, \rho_0^B)] - \frac{4R_{\max}\gamma}{(1-\gamma)^2} \beta - \frac{2R_{\max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[\mathbb{E}[\gamma^{T_{\mathcal{V}}^\pi}]] - \frac{2R_{\max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[\mathbb{E}[\gamma^{T_{\mathcal{V}}^{\pi^*}}]] \quad (21)$$

□

## A.2 PROOF OF THEOREM 2

We begin by highlighting the performance divergence of a risk-aware policy between the offline dataset and the true environment, represented by the universal uncertainty set, in Lemma 3. Within this lemma, the term  $\beta - p_r \beta_r$  underscores the narrowed performance gap achieved by incorporating robustness into the modeling. This foundational understanding sets the stage for the detailed proof in Theorem 2.

**Lemma 3. [Risk-Aware Policy Reality Gap: Performance Gap between Risk-Aware Uncertainty Set and Reality (the universal uncertainty set)]** Given a robust policy  $\pi_r$  such that  $\pi_r = \arg \max_{\pi} \mathbb{E}_{P \sim \mathcal{U}_r} J_{\rho}(\pi, P)$  and  $\mathbb{E}_{P \sim \mathcal{U}_r}(\mathbb{E}_{s,a} D_{TV}(P, P_B)) \leq \beta_r$ . Considering the fact that there might be randomness that we cannot capture during training, we assume  $\mathcal{U}_r \subseteq \mathcal{U}$ ,  $\beta \geq \beta_r$ , and the probability of  $P \in \mathcal{U}_r$  for every  $P \in \mathcal{U}$  is  $p_r$  where  $0 \leq p_r \leq 1$ . The performance on the uncertain nominal transition kernel set  $\mathcal{U}$  and the training transition kernel set  $\mathcal{U}_r$  satisfies:

$$\begin{aligned} \mathbb{E}_{P_r \sim \mathcal{U}_r}[J_{\rho_0^B}(\pi_r, P_r)] &\geq \mathbb{E}_{P_0 \sim \mathcal{U}}[J_{\rho_0}(\pi_r, P_0)] - \frac{2R_{\max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[D_{TV}(\rho_0, \rho_0^B)] \\ &\quad - \frac{2\gamma R_{\max}}{(1-\gamma)^2} (\beta - p_r \beta_r) - \frac{2R_{\max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[\mathbb{E}[\gamma^{T_{\mathcal{V}}^{\pi_r}}]] \end{aligned} \quad (22)$$

$$\begin{aligned} \mathbb{E}_{P_r \sim \mathcal{U}_r}[J_{\rho_0^B}(\pi_r, P_r)] &\leq \mathbb{E}_{P_0 \sim \mathcal{U}}[J_{\rho_0}(\pi_r, P_0)] + \frac{2R_{\max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[D_{TV}(\rho_0, \rho_0^B)] \\ &\quad + \frac{2\gamma R_{\max}}{(1-\gamma)^2} \beta + \frac{2R_{\max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[\mathbb{E}[\gamma^{T_{\mathcal{V}}^{\pi_r}}]], \end{aligned} \quad (23)$$

where  $\mathcal{V}$  is an unknown state action set defined as:  $(s, a) \in \mathcal{V}$  iff  $(s, a)$  is not in the offline dataset and  $T_{\mathcal{V}}^{\pi_r}$  denotes the hitting time of unknown states.

*Proof.* Building upon the insights and methodology established in the proof of Lemma 11, we now turn our attention to a new set of dynamics. In this context, we compare the performance of a policy  $\pi$  across two distinct transition dynamics:  $P_r \sim \mathcal{U}_r$  and  $P_0 \sim \mathcal{U}$ . By leveraging the foundational ideas from the aforementioned theorem, we aim to unravel the performance disparities between these two MDPs, especially focusing on the divergence arising from known state-action pairs in the dataset and those that remain unidentified (unknown).

For states that are in the dataset, we can establish a relationship based on the definition of the uncertainty set. Specifically:

$$\mathbb{E}_{P_0 \sim \mathcal{U}} \mathbb{E}_{P_r \sim \mathcal{U}_r} (\|P_0(s, a) - P_r(s, a)\|_1) \leq \max(\beta, \beta_r) = \beta.$$

From this relation, it becomes straightforward to deduce the upper-bound performance of a robust policy. On the other hand, when considering the lower-bound performance of a robust policy, defined as

$$\pi_r = \arg \max_{\pi} \mathbb{E}_{P \sim \mathcal{U}_r} J_{\rho}(\pi, P),$$

subject to the constraint

$$\mathbb{E}_{P \sim \mathcal{U}_r} [\mathbb{E}_{s,a} D_{TV}(P, P_B)] \leq \beta_r.$$

The "untrained" region is quantified by the difference  $(1 - p_r)\beta + p_r(\beta - \beta_r) = \beta - p_r\beta_r$ .

Under these conditions, it's clear that the probability of disadvantageous scenarios for the robust policy at each step is  $1 - (\beta - p_r\beta_r)$ . Consequently, the chance of decoupling at a specific time  $t$  is at most  $1 - (1 - (\beta - p_r\beta_r))^t$ . Then we have:

$$\mathbb{E}_{P_r \sim \mathcal{U}_r} J_{\rho_0^B}(\pi_r, P_r) - \mathbb{E}_{P_0 \sim \mathcal{U}} J_{\rho_0}(\pi_r, P_0) \quad (24)$$

$$\geq \frac{2R_{\max}}{1 - \gamma} \mathbb{E}_{P_0 \sim \mathcal{U}} [D_{TV}(\rho_0, \rho_0^B)] + \sum_t \gamma^t (1 - (1 - (\beta - p_r\beta_r))^t) \cdot 2 \cdot R_{\max} + \frac{2R_{\max}}{1 - \gamma} \mathbb{E}_{P_0 \sim \mathcal{U}} [\gamma^{T_{\mathcal{V}}^{\pi_r}}] \quad (25)$$

$$\geq \frac{2R_{\max}}{1 - \gamma} \mathbb{E}_{P_0 \sim \mathcal{U}} [D_{TV}(\rho_0, \rho_0^B)] + \frac{2R_{\max}\gamma(\beta - p_r\beta_r)}{(1 - \gamma)(1 - \gamma \cdot (1 - (\beta - p_r\beta_r)))} + \frac{2R_{\max}}{1 - \gamma} \mathbb{E}_{P_0 \sim \mathcal{U}} [\gamma^{T_{\mathcal{V}}^{\pi_r}}] \quad (26)$$

$$\geq \frac{2R_{\max}}{1 - \gamma} \mathbb{E}_{P_0 \sim \mathcal{U}} [D_{TV}(\rho_0, \rho_0^B)] + \frac{2R_{\max}\gamma}{(1 - \gamma)^2} (\beta - p_r\beta_r) + \frac{2R_{\max}}{1 - \gamma} \mathbb{E}_{P_0 \sim \mathcal{U}} [\gamma^{T_{\mathcal{V}}^{\pi_r}}] \quad (27)$$

□

For ease of exposition, we restate Theorem 2 as follows.

**Theorem 2.** For an  $\epsilon_{\pi_r}$  sub-optimal risk-aware policy, we have:

$$\begin{aligned} \mathbb{E}_{P_0 \sim \mathcal{U}} [J_{\rho_0}(\pi^*, P_0)] - \mathbb{E}_{P_0 \sim \mathcal{U}} [J_{\rho_0}(\pi_r, P_0)] &\leq \epsilon_{\pi_r} + \frac{4R_{\max}}{1 - \gamma} \mathbb{E}_{P_0 \sim \mathcal{U}} [D_{TV}(\rho_0, \rho_0^B)] + \frac{4\gamma R_{\max}}{(1 - \gamma)^2} (\beta - \frac{1}{2} p_r\beta_r) \\ &\quad + \frac{2R_{\max}}{1 - \gamma} \mathbb{E}_{P_0 \sim \mathcal{U}} [\gamma^{T_{\mathcal{V}}^{\pi_r}}] + \frac{2R_{\max}}{1 - \gamma} \mathbb{E}_{P_0 \sim \mathcal{U}} [\gamma^{T_{\mathcal{V}}^{\pi^*}}]. \end{aligned} \quad (28)$$

*Proof.* By Lemma 3 we have:

$$\begin{aligned} \mathbb{E}_{P_0 \sim \mathcal{U}} [J_{\rho_0}(\pi_r, P_0)] &\geq J_{\rho_0^B}(\pi_r, P_B) - \frac{2R_{\max}}{1 - \gamma} \mathbb{E}_{P_0 \sim \mathcal{U}} [D_{TV}(\rho_0, \rho_0^B)] - \frac{2R_{\max}\gamma}{(1 - \gamma)^2} \beta - \frac{2R_{\max}}{1 - \gamma} \mathbb{E}_{P_0 \sim \mathcal{U}} [\gamma^{T_{\mathcal{V}}^{\pi_r}}] \\ &\geq J_{\rho_0^B}(\pi^*, P_B) - \epsilon_{\pi_r} \end{aligned} \quad (29)$$

$$\begin{aligned} &\quad - \frac{2R_{\max}}{1 - \gamma} \mathbb{E}_{P_0 \sim \mathcal{U}} [D_{TV}(\rho_0, \rho_0^B)] - \frac{2R_{\max}\gamma}{(1 - \gamma)^2} \beta - \frac{2R_{\max}}{1 - \gamma} \mathbb{E}_{P_0 \sim \mathcal{U}} [\gamma^{T_{\mathcal{V}}^{\pi_r}}] \end{aligned} \quad (30)$$

$$\geq \mathbb{E}_{P_0 \sim \mathcal{U}} [J_{\rho_0}(\pi^*, P_0)] - \epsilon_{\pi_r} \quad (31)$$

$$\begin{aligned} &\quad - \frac{4R_{\max}}{1 - \gamma} \mathbb{E}_{P_0 \sim \mathcal{U}} [D_{TV}(\rho_0, \rho_0^B)] - \frac{4R_{\max}\gamma}{(1 - \gamma)^2} (\beta - \frac{1}{2} p_r\beta_r) - \frac{2R_{\max}}{1 - \gamma} \mathbb{E}_{P_0 \sim \mathcal{U}} [\gamma^{T_{\mathcal{V}}^{\pi_r}}] \end{aligned} \quad (32)$$

$$\begin{aligned} &\quad - \frac{2R_{\max}}{1 - \gamma} \mathbb{E}_{P_0 \sim \mathcal{U}} [\gamma^{T_{\mathcal{V}}^{\pi^*}}] \end{aligned} \quad (33)$$

□

## A.3 PROOF OF THEOREM 3

**Theorem 3.** *[Relaxed State-Adversarial Policy Performance Lower Bound] For an  $\epsilon_{\pi_{RA}}$  sub-optimal relaxed state-adversarial Policy policy, we have*

$$\begin{aligned} \mathbb{E}_{P_0 \sim \mathcal{U}}[J_{\rho_0}(\pi^*, P_0)] - \mathbb{E}_{P_0 \sim \mathcal{U}}[J_{\rho_0}(\pi_{RA}, P_0)] &\leq \epsilon_{\pi_{RA}} + \frac{4R_{max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[D_{TV}(\rho_0, \rho_0^B)] \\ &\quad + \frac{4\gamma R_{max}}{(1-\gamma)^2} (\beta - \frac{1}{2} p_{RA}(1-\alpha)) + \frac{2R_{max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[\gamma^{T_{\mathcal{V}}^{\pi_{RA}}}] \\ &\quad + \frac{2R_{max}}{1-\gamma} \mathbb{E}_{P_0 \sim \mathcal{U}}[\gamma^{T_{\mathcal{V}}^{\pi^*}}]. \end{aligned} \quad (34)$$

*Proof.* Consider the relaxed state-adversarial policy:

$$\pi_{RA} = \arg \max_{\pi} \mathbb{E}_{P \sim \mathcal{U}_{\epsilon}^{\pi}} J_{\rho}(\pi, P),$$

subject to the constraint:

$$\mathbb{E}_{P \sim \mathcal{U}_{\epsilon}^{\pi}} (\mathbb{E}_{s,a} D_{TV}(P, P_B)) \leq 1 - \alpha.$$

By setting  $\beta_r = 1 - \alpha$  and  $p_r = p_{RA}$ , we can directly apply Theorem 3. This leads us to the desired assertion, thereby completing the proof.  $\square$