

Supplementary Materials

A Q-sampling Algorithm

In this section, we provide the formal description for the algorithm EstQ in Algorithm 3, which returns an unbiased estimation of the state-action value function (Q-value).

Algorithm 3 EstQ (Zhang et al., 2019)

```

1: Input:  $s, a, \theta$ . Initialize  $\hat{Q} = 0, s_1^q = s, a_1^q = a$ 
2: Draw  $T \sim \text{Geom}(1 - \gamma^{1/2})$ 
3: for  $t = 1, 2, \dots, T - 1$  do
4:   Collect reward  $R(s_t^q, a_t^q)$  and update the Q-function  $\hat{Q} \leftarrow \hat{Q} + \gamma^{t/2} R(s_t^q, a_t^q)$ 
5:   Sample  $s_{t+1}^q \sim \mathbb{P}(\cdot | s_t^q, a_t^q), a_{t+1}^q \sim \pi_\theta(\cdot | s_{t+1}^q)$ 
6: end for
7: Collect reward  $R(s_T^q, a_T^q)$  and update the Q-function  $\hat{Q} \leftarrow \hat{Q} + \gamma^{T/2} R(s_T^q, a_T^q)$ 
8: Output:  $\hat{Q}^{\pi_\theta} \leftarrow \hat{Q}$ 
```

B Proof of Proposition 1

In this section, we first provide two useful lemmas, which establish the smoothness property of the visitation distribution and Q-function.

Lemma 1. ((Xu et al., 2020a, Lemma 3)) Consider the initial distribution $\xi(\cdot)$ and the transition kernel $\mathbf{P}(\cdot | s, a)$. Let $\xi(\cdot)$ be $\zeta(\cdot)$ or $\mathbf{P}(\cdot | \hat{s}, \hat{a})$ for any given $\hat{s} \in \mathcal{S}, \hat{a} \in \mathcal{A}$. Denote $\nu_{\pi_\theta, \xi}$ as the state-action visitation distribution of MDP with policy π_θ and the initialization distribution ξ . Suppose Assumption 3 holds. Then we have, under direct parameterization for any $\theta_1, \theta_2 \in \Theta_p$,

$$\|\nu_{\pi_\theta, \xi} - \nu_{\pi_{\theta'}, \xi}\|_{TV} \leq C_\nu \|\theta_1 - \theta_2\|_2,$$

where $C_\nu = \frac{\sqrt{|\mathcal{A}|}}{2} (1 + \lceil \log_\rho C_M^{-1} \rceil + (1 - \rho)^{-1})$.

Lemma 2. ((Xu et al., 2020a, Lemma 4)) Suppose Assumptions 3 and 4 hold. Let Q_α^π denote the Q-function of policy π under the reward function r_α . For any state-action pair $(s, a) \in \mathcal{S} \times \mathcal{A}$, $\alpha \in \Lambda$ and $\theta_1, \theta_2 \in \Theta_p$ (under direct parameterization), we have

$$|Q_\alpha^{\pi_{\theta_1}}(s, a) - Q_\alpha^{\pi_{\theta_2}}(s, a)| \leq L_Q \|\theta_1 - \theta_2\|_2,$$

where $L_Q = \frac{2C_r C_\alpha C_\nu}{1-\gamma}$ and C_ν is defined in Lemma 1.

Denote $d_\pi(s) = (1 - \gamma) \sum_{t=0}^{\infty} \gamma^t \mathbb{P}\{s_t = s | \pi\}$ as the state visitation distribution induced by policy π . We next prove Proposition 1 to characterize the Lipschitz constants L_{11}, L_{12}, L_{21} and L_{22} , respectively.

Proof of Proposition 1. We consider the first inequality in Proposition 1:

$$\begin{aligned}
 \|\nabla_\theta F(\theta_1, \alpha_1) - \nabla_\theta F(\theta_2, \alpha_2)\|_2 &= \|\nabla_\theta F(\theta_1, \alpha_1) - \nabla_\theta F(\theta_2, \alpha_1) + \nabla_\theta F(\theta_2, \alpha_1) - \nabla_\theta F(\theta_2, \alpha_2)\|_2 \\
 &\leq \underbrace{\|\nabla_\theta F(\theta_1, \alpha_1) - \nabla_\theta F(\theta_2, \alpha_1)\|_2}_{T_1} + \underbrace{\|\nabla_\theta F(\theta_2, \alpha_1) - \nabla_\theta F(\theta_2, \alpha_2)\|_2}_{T_2}. \tag{9}
 \end{aligned}$$

Next, we upper-bound the terms T_1 and T_2 in eq. (9), respectively.

Upper-bounding T_1 : For any given state-action pair $(s, a) \in \mathcal{S} \times \mathcal{A}$, we have

$$\begin{aligned}
 & \left| (\nabla_\theta F(\theta_1, \alpha_1) - \nabla_\theta F(\theta_2, \alpha_1))_{s,a} \right| \\
 & \stackrel{(i)}{=} \left| \frac{1}{1-\gamma} (d_{\pi_{\theta_1}}(s) Q_{\alpha_1}^{\pi_{\theta_1}}(s, a) - d_{\pi_{\theta_2}}(s) Q_{\alpha_1}^{\pi_{\theta_2}}(s, a)) \right| \\
 & \leq \left| \frac{1}{1-\gamma} ((d_{\pi_{\theta_1}}(s) - d_{\pi_{\theta_2}}(s)) Q_{\alpha_1}^{\pi_{\theta_1}}(s, a)) \right| + \left| \frac{1}{1-\gamma} (d_{\pi_{\theta_2}}(s) (Q_{\alpha_1}^{\pi_{\theta_1}}(s, a) - Q_{\alpha_1}^{\pi_{\theta_2}}(s, a))) \right| \\
 & \stackrel{(ii)}{\leq} \frac{R_{max}}{(1-\gamma)^2} |d_{\pi_{\theta_1}}(s) - d_{\pi_{\theta_2}}(s)| + \frac{L_Q}{1-\gamma} d_{\pi_{\theta_2}}(s) \|\theta_1 - \theta_2\|_2,
 \end{aligned} \tag{10}$$

where (i) follows from the fact that $\frac{\partial F(\theta, \alpha_1)}{\partial \theta_{s,a}} = -\frac{\partial V(\pi_\theta, \alpha_1)}{\partial \theta_{s,a}} = -\frac{1}{1-\gamma} d_{\pi_\theta}(s) Q_{\alpha_1}^{\pi_\theta}(s, a)$, and (ii) follows from Lemma 2.

Then, we proceed as follows:

$$\begin{aligned}
 & \|\nabla_\theta F(\theta_1, \alpha_1) - \nabla_\theta F(\theta_2, \alpha_1)\|_2 \\
 &= \sqrt{\sum_{s,a} \left| (\nabla_\theta F(\theta_1, \alpha_1) - \nabla_\theta F(\theta_2, \alpha_1))_{s,a} \right|^2} \\
 &\stackrel{(i)}{\leq} \sqrt{\sum_{s,a} \left(\frac{R_{max}}{(1-\gamma)^2} |d_{\pi_{\theta_1}}(s) - d_{\pi_{\theta_2}}(s)| + \frac{L_Q}{1-\gamma} d_{\pi_{\theta_2}}(s) \|\theta_1 - \theta_2\|_2 \right)^2} \\
 &\leq \sqrt{2|\mathcal{A}|} \sqrt{\sum_s \left(\frac{R_{max}}{(1-\gamma)^2} |d_{\pi_{\theta_1}}(s) - d_{\pi_{\theta_2}}(s)| \right)^2} + \sqrt{2|\mathcal{A}|} \sqrt{\sum_s \left(\frac{L_Q}{1-\gamma} d_{\pi_{\theta_2}}(s) \|\theta_1 - \theta_2\|_2 \right)^2} \\
 &\stackrel{(ii)}{\leq} \sqrt{2|\mathcal{A}|} \left(\sum_s \frac{R_{max}}{(1-\gamma)^2} |d_{\pi_{\theta_1}}(s) - d_{\pi_{\theta_2}}(s)| + \sum_s \frac{L_Q}{1-\gamma} d_{\pi_{\theta_2}}(s) \|\theta_1 - \theta_2\|_2 \right) \\
 &\stackrel{(iii)}{\leq} \frac{2\sqrt{2}|\mathcal{A}|C_r C_\alpha}{(1-\gamma)^2} (1 + \lceil \log_\rho C_M^{-1} \rceil + (1-\rho)^{-1}) \|\theta_1 - \theta_2\|_2,
 \end{aligned}$$

where (i) follows from eq. (10), (ii) follows from the fact that $\|x\|_2 \leq \|x\|_1$, and (iii) follows from Lemma 1 and from the facts $R_{max} \leq C_r C_\alpha$ and

$$\sum_{s \in \mathcal{S}} |d_{\pi_{\theta_1}}(s) - d_{\pi_{\theta_2}}(s)| = 2 \|d_{\pi_{\theta_1}} - d_{\pi_{\theta_2}}\|_{TV} \leq 2 \|\nu_{\pi_{\theta_1}} - \nu_{\pi_{\theta_2}}\|_{TV}.$$

Upper-bounding T_2 : For any given state-action pair $(s, a) \in \mathcal{S} \times \mathcal{A}$, we have

$$\begin{aligned}
 & \left| (\nabla_\theta F(\theta_2, \alpha_1) - \nabla_\theta F(\theta_2, \alpha_2))_{s,a} \right| = \left| \frac{1}{1-\gamma} (d_{\pi_{\theta_2}}(s) Q_{\alpha_1}^{\pi_{\theta_2}}(s, a) - d_{\pi_{\theta_2}}(s) Q_{\alpha_2}^{\pi_{\theta_2}}(s, a)) \right| \\
 & \stackrel{(i)}{=} \frac{1}{1-\gamma} d_{\pi_{\theta_2}}(s) \left| \frac{1}{1-\gamma} \sum_{\hat{s}, \hat{a}} \nu_{\pi_{\theta_2}, s, a}(\hat{s}, \hat{a}) (r_{\alpha_1}(\hat{s}, \hat{a}) - r_{\alpha_2}(\hat{s}, \hat{a})) \right| \\
 & \stackrel{(ii)}{\leq} \frac{1}{(1-\gamma)^2} d_{\pi_{\theta_2}}(s) C_r \|\alpha_1 - \alpha_2\|_2,
 \end{aligned}$$

where in (i) we denote $\nu_{\pi_{\theta_2}, s, a}(\hat{s}, \hat{a})$ as the visitation distribution of the Markov chain with initial distribution $\mathbb{P}(\cdot | s_0 = s, a_0 = a)$ and policy π_{θ_2} , and (ii) follows from the fact that $|r_{\alpha_1}(\hat{s}, \hat{a}) - r_{\alpha_2}(\hat{s}, \hat{a})| = |\langle \nabla_\alpha r_{\alpha'}(\hat{s}, \hat{a}), \alpha_1 - \alpha_2 \rangle| \leq \|\nabla_\alpha r_{\alpha'}(\hat{s}, \hat{a})\|_2 \|\alpha_1 - \alpha_2\|_2 \leq C_r \|\alpha_1 - \alpha_2\|_2$, for some $\alpha' \in [\alpha_1, \alpha_2]$. The inequality above implies that

$$\|\nabla_\theta F(\theta_2, \alpha_1) - \nabla_\theta F(\theta_2, \alpha_2)\|_2 = \sqrt{\sum_{s,a} \left| (\nabla_\theta F(\theta_2, \alpha_1) - \nabla_\theta F(\theta_2, \alpha_2))_{s,a} \right|^2}$$

$$\begin{aligned}
 &\leq \sqrt{\sum_{s,a} \left(\frac{1}{(1-\gamma)^2} d_{\pi_{\theta_2}}(s) C_r \|\alpha_1 - \alpha_2\|_2 \right)^2} \\
 &= \frac{\sqrt{|\mathcal{A}|} C_r}{(1-\gamma)^2} \|\alpha_1 - \alpha_2\|_2 \sqrt{\sum_s (d_{\pi_{\theta_2}}(s))^2} \\
 &\stackrel{(i)}{\leq} \frac{\sqrt{|\mathcal{A}|} C_r}{(1-\gamma)^2} \|\alpha_1 - \alpha_2\|_2,
 \end{aligned}$$

where (i) follows from the fact that $\sqrt{\sum_s (d_{\pi_{\theta_2}}(s))^2} \leq \|d_{\pi_{\theta_2}}\|_1 = 1$.

Therefore we obtain the upper bound of eq. (9) as follows:

$$\|\nabla_{\theta} F(\theta_1, \alpha_1) - \nabla_{\theta} F(\theta_2, \alpha_2)\|_2 \leq \frac{2\sqrt{2}|\mathcal{A}|C_rC_{\alpha}}{(1-\gamma)^2} (1 + \lceil \log_{\rho} C_M^{-1} \rceil + (1-\rho)^{-1}) \|\theta_1 - \theta_2\|_2 + \frac{\sqrt{|\mathcal{A}|}C_r}{(1-\gamma)^2} \|\alpha_1 - \alpha_2\|_2,$$

which determines the constants L_{11} and L_{12} .

We then proceed to prove the second inequality in Proposition 1.

$$\begin{aligned}
 \|\nabla_{\alpha} F(\theta_1, \alpha_1) - \nabla_{\alpha} F(\theta_2, \alpha_2)\|_2 &\leq \|\nabla_{\alpha} F(\theta_1, \alpha_1) - \nabla_{\alpha} F(\theta_2, \alpha_1) + \nabla_{\alpha} F(\theta_2, \alpha_1) - \nabla_{\alpha} F(\theta_2, \alpha_2)\|_2 \\
 &\leq \underbrace{\|\nabla_{\alpha} F(\theta_1, \alpha_1) - \nabla_{\alpha} F(\theta_2, \alpha_1)\|_2}_{T_3} + \underbrace{\|\nabla_{\alpha} F(\theta_2, \alpha_1) - \nabla_{\alpha} F(\theta_2, \alpha_2)\|_2}_{T_4}. \quad (11)
 \end{aligned}$$

Next, we upper-bound T_3 and T_4 in eq. (11), respectively.

Upper-bounding T_3 : For any given $1 \leq i \leq q$, we have

$$\begin{aligned}
 &|(\nabla_{\alpha} F(\theta_1, \alpha_1) - \nabla_{\alpha} F(\theta_2, \alpha_1))_i| \\
 &= |(\nabla_{\alpha} V(\pi_E, r_{\alpha_1}) - \nabla_{\alpha} V(\pi_{\theta_1}, r_{\alpha_1}) - \nabla_{\alpha} \psi(\alpha_1) - (\nabla_{\alpha} V(\pi_E, r_{\alpha_1}) - \nabla_{\alpha} V(\pi_{\theta_2}, r_{\alpha_1}) - \nabla_{\alpha} \psi(\alpha_1)))_i| \\
 &= |(\nabla_{\alpha} V(\pi_{\theta_2}, r_{\alpha_1}) - \nabla_{\alpha} V(\pi_{\theta_1}, r_{\alpha_1}))_i| \\
 &= \frac{1}{1-\gamma} \left| \sum_{s,a} (\nu_{\pi_{\theta_1}}(s, a) - \nu_{\pi_{\theta_2}}(s, a)) (\nabla_{\alpha} r_{\alpha_1})_i \right| \leq \frac{\|\nu_{\pi_{\theta_1}} - \nu_{\pi_{\theta_2}}\|_1 \left\| \frac{\partial r_{\alpha}}{\partial \alpha_i} \right\|_{\infty}}{1-\gamma} \\
 &\stackrel{(i)}{\leq} \frac{2C_{\nu} \|\theta_1 - \theta_2\|_2 \left\| \frac{\partial r_{\alpha}}{\partial \alpha_i} \right\|_{\infty}}{1-\gamma},
 \end{aligned}$$

where (i) follows from Lemma 1 and the fact that $\|p - q\|_1 = 2\|p - q\|_{TV}$. The inequality above further implies that

$$\begin{aligned}
 \|\nabla_{\alpha} F(\theta_1, \alpha) - \nabla_{\alpha} F(\theta_2, \alpha)\|_2 &\leq \frac{2C_{\nu} \|\theta_1 - \theta_2\|_2}{1-\gamma} \sqrt{\sum_{i=1}^q \left\| \frac{\partial r_{\alpha}}{\partial \alpha_i} \right\|_{\infty}^2} \\
 &\leq \frac{C_r \sqrt{|\mathcal{A}|}}{1-\gamma} (1 + \lceil \log_{\rho} C_M^{-1} \rceil + (1-\rho)^{-1}) \|\theta_1 - \theta_2\|_2.
 \end{aligned}$$

Upper-bounding T_4 : We provide a proof for the general parameterization of policy, which includes the direct parameterization of policy as a special case and covers the last claim of Proposition 1. We proceed as follows:

$$\begin{aligned}
 &\|\nabla_{\alpha} F(\theta_2, \alpha_1) - \nabla_{\alpha} F(\theta_2, \alpha_2)\|_2 \\
 &\leq \|\nabla_{\alpha} V(\pi_E, r_{\alpha_1}) - \nabla_{\alpha} V(\pi_{\theta_2}, r_{\alpha_1}) - \nabla_{\alpha} \psi(\alpha_1) - (\nabla_{\alpha} V(\pi_E, r_{\alpha_2}) - \nabla_{\alpha} V(\pi_{\theta_2}, r_{\alpha_2}) - \nabla_{\alpha} \psi(\alpha_2))\|_2 \\
 &\leq \frac{1}{1-\gamma} \left(\left\| \int (\nabla_{\alpha} r_{\alpha_1} - \nabla_{\alpha} r_{\alpha_2}) d\nu_{\pi_E} \right\|_2 + \left\| \int (\nabla_{\alpha} r_{\alpha_1} - \nabla_{\alpha} r_{\alpha_2}) d\nu_{\pi_{\theta_2}} \right\|_2 \right) + \|\nabla_{\alpha} \psi(\alpha_1) - \nabla_{\alpha} \psi(\alpha_2)\|_2 \\
 &= \frac{1}{1-\gamma} \left(\sqrt{\sum_{i=1}^q \left(\int (\nabla_{\alpha} r_{\alpha_1}(s, a) - \nabla_{\alpha} r_{\alpha_2}(s, a))_i d\nu_{\pi_E} \right)^2} + \sqrt{\sum_{i=1}^q \left(\int (\nabla_{\alpha} r_{\alpha_1}(s, a) - \nabla_{\alpha} r_{\alpha_2}(s, a))_i d\nu_{\pi_{\theta_2}} \right)^2} \right)
 \end{aligned}$$

$$\begin{aligned}
 & + \|\nabla_\alpha \psi(\alpha_1) - \nabla_\alpha \psi(\alpha_2)\|_2 \\
 & \stackrel{(i)}{\leq} \left(\frac{2\sqrt{q}L_r}{1-\gamma} + L_\psi \right) \|\alpha_1 - \alpha_2\|_2,
 \end{aligned}$$

where (i) follows from Assumption 1 and further because for any (s, a) and i , we have

$$|(\nabla_\alpha r_{\alpha_1}(s, a) - \nabla_\alpha r_{\alpha_2}(s, a))_i| \leq \|\nabla_\alpha r_{\alpha_1}(s, a) - \nabla_\alpha r_{\alpha_2}(s, a)\|_2 \leq L_r \|\alpha_1 - \alpha_2\|_2.$$

Therefore, we obtain the following upper bound in eq. (11)

$$\begin{aligned}
 & \|\nabla_\alpha F(\theta_1, \alpha_1) - \nabla_\alpha F(\theta_2, \alpha_2)\|_2 \\
 & \leq \frac{C_r \sqrt{|\mathcal{A}|}}{1-\gamma} \left(1 + \lceil \log_\rho C_M^{-1} \rceil + (1-\rho)^{-1} \right) \|\theta_1 - \theta_2\|_2 + \left(\frac{2\sqrt{q}L_r}{1-\gamma} + L_\psi \right) \|\alpha_1 - \alpha_2\|_2,
 \end{aligned}$$

which determines L_{21} and L_{22} . \square

C Proof of Proposition 2

We define $\theta_{op}(\alpha) := \operatorname{argmin}_{\theta \in \Theta_p} F(\theta, \alpha)$. If there exist multiple optimal points, then $\theta_{op}(\alpha)$ can be any optimal point.

We first provide a lemma, which characterizes the gradient dominance property for the function $F(\theta, \alpha)$ with a fixed reward parameter α .

Lemma 3. ((Agarwal et al., 2019, Lemma 4.1)) *For any given $\alpha \in \Lambda$, $F(\theta, \alpha)$ defined in eq. (1) with direct parameterization satisfies,*

$$F(\theta, \alpha) - F(\theta_{op}(\alpha), \alpha) \leq C_d \max_{\tilde{\theta} \in \Theta_p} \langle \theta - \tilde{\theta}, \nabla_\theta F(\theta, \alpha) \rangle,$$

where $C_d = \frac{1}{(1-\gamma) \min_s \{\zeta(s)\}}$.

We then provide the proof of Proposition 2.

Proof of Proposition 2. We proceed as follows:

$$\begin{aligned}
 g(\theta) - g(\theta^*) &= F(\theta, \alpha_{op}(\theta)) - F(\theta^*, \alpha_{op}(\theta^*)) \\
 &= F(\theta, \alpha_{op}(\theta)) - F(\theta_{op}(\alpha_{op}(\theta)), \alpha_{op}(\theta)) + F(\theta_{op}(\alpha_{op}(\theta)), \alpha_{op}(\theta)) - F(\theta^*, \alpha_{op}(\theta^*)) \\
 &\stackrel{(i)}{\leq} F(\theta, \alpha_{op}(\theta)) - F(\theta_{op}(\alpha_{op}(\theta)), \alpha_{op}(\theta)) \\
 &\stackrel{(ii)}{\leq} C_d \max_{\tilde{\theta} \in \Theta_p} \langle \theta - \tilde{\theta}, \nabla_\theta F(\theta, \alpha_{op}(\theta)) \rangle \\
 &\stackrel{(iii)}{=} C_d \max_{\tilde{\theta} \in \Theta_p} \langle \theta - \tilde{\theta}, \nabla g(\theta) \rangle,
 \end{aligned}$$

where (i) follows from the fact that

$$\begin{aligned}
 & F(\theta_{op}(\alpha_{op}(\theta)), \alpha_{op}(\theta)) - F(\theta^*, \alpha_{op}(\theta^*)) \\
 &= \underbrace{F(\theta_{op}(\alpha_{op}(\theta)), \alpha_{op}(\theta)) - F(\theta^*, \alpha_{op}(\theta))}_{\leq 0} + \underbrace{F(\theta^*, \alpha_{op}(\theta)) - F(\theta^*, \alpha_{op}(\theta^*))}_{\leq 0} \leq 0,
 \end{aligned}$$

(ii) follows from Lemma 3, and (iii) follows because $\nabla g(\theta) = \nabla_\theta F(\theta, \alpha)|_{\alpha=\alpha_{op}(\theta)}$. \square

D Supporting Lemmas for GAIL Framework

In this section, we establish two supporting lemmas that are useful for the proof of our main theorems.

Lemma 4. *Suppose Assumption 3 holds. Consider the gradient approximation in the nested-loop GAIL framework (Algorithm 1). For any k and t , $0 \leq k \leq K - 1$ and $0 \leq t \leq T - 1$, we have*

$$\mathbb{E} \left[\left\| \widehat{\nabla}_\alpha F(\theta_t, \alpha_k^t) - \nabla_\alpha F(\theta_t, \alpha_k^t) \right\|_2^2 \right] \leq \frac{16C_r^2}{1-\gamma} \left(1 + \frac{C_M}{1-\rho} \right) \frac{1}{B}.$$

Proof of Lemma 4. We denote $d_\pi(s) := (1-\gamma) \sum_{t=0}^{\infty} \gamma^t \mathbb{P}\{s_t = s\}$ as the state visitation distribution of the Markov chain with initial distribution $\zeta(\cdot)$, transition kernel $P(\cdot|s, a)$ and policy π . Both trajectories $(s_0^E, a_0^E, s_1^E, a_1^E, \dots, s_i^E, a_i^E)$ and $(s_0^\theta, a_0^\theta, s_1^\theta, a_1^\theta, \dots, s_i^\theta, a_i^\theta)$ are sampled under the transition kernel $\tilde{P}(\cdot|s, a) = \gamma P(\cdot|s, a) + (1-\gamma)\zeta(\cdot)$. Recall that it has been shown in Konda (2002) that the stationary distribution of the Markov chain with transition kernel and policy π is d_π .

By definition, we have,

$$\begin{aligned} & \mathbb{E} \left[\left\| \widehat{\nabla}_\alpha F(\theta_t, \alpha_k^t) - \nabla_\alpha F(\theta_t, \alpha_k^t) \right\|_2^2 \right] \\ &= \mathbb{E} \left[\left\| \frac{1}{(1-\gamma)B} \left(\sum_{i=0}^{B-1} \nabla_{\alpha_k^t} r_{\alpha_k^t}(s_i^E, a_i^E) - \nabla_{\alpha_k^t} r_{\alpha_k^t}(s_i^\theta, a_i^\theta) \right) - \frac{1}{1-\gamma} \left(\mathbb{E}_{(s,a) \sim \nu_{\pi_E}} [\nabla_{\alpha_k^t} r_{\alpha_k^t}(s, a)] - \mathbb{E}_{(s,a) \sim \nu_{\pi_{\theta_t}}} [\nabla_{\alpha_k^t} r_{\alpha_k^t}(s, a)] \right) \right\|_2^2 \right] \\ &\leq \frac{2}{(1-\gamma)^2 B^2} \mathbb{E} \underbrace{\left[\left\| \sum_{i=0}^{B-1} \left(\nabla_{\alpha_k^t} r_{\alpha_k^t}(s_i^E, a_i^E) - \mathbb{E}_{(s,a) \sim \nu_{\pi_E}} [\nabla_{\alpha_k^t} r_{\alpha_k^t}(s, a)] \right) \right\|_2^2 \right]}_{T_1} \\ &\quad + \frac{2}{(1-\gamma)^2 B^2} \mathbb{E} \underbrace{\left[\left\| \sum_{i=0}^{B-1} \left(\nabla_{\alpha_k^t} r_{\alpha_k^t}(s_i^\theta, a_i^\theta) - \mathbb{E}_{(s,a) \sim \nu_{\pi_{\theta_t}}} [\nabla_{\alpha_k^t} r_{\alpha_k^t}(s, a)] \right) \right\|_2^2 \right]}_{T_2}. \end{aligned} \tag{12}$$

We first provide an upper bound on the term T_1 in eq. (12), and proceed as follows:

$$\begin{aligned} T_1 &= \sum_{i=0}^{B-1} \mathbb{E} \left\| \nabla_{\alpha_k^t} r_{\alpha_k^t}(s_i^E, a_i^E) - \mathbb{E}_{(s,a) \sim \nu_{\pi_E}} [\nabla_{\alpha_k^t} r_{\alpha_k^t}(s, a)] \right\|_2^2 \\ &\quad + \sum_{i \neq j} \mathbb{E} \left\langle \nabla_{\alpha_k^t} r_{\alpha_k^t}(s_i^E, a_i^E) - \mathbb{E}_{(s,a) \sim \nu_{\pi_E}} [\nabla_{\alpha_k^t} r_{\alpha_k^t}(s, a)], \nabla_{\alpha_k^t} r_{\alpha_k^t}(s_j^E, a_j^E) - \mathbb{E}_{(s,a) \sim \nu_{\pi_E}} [\nabla_{\alpha_k^t} r_{\alpha_k^t}(s, a)] \right\rangle \\ &\leq 4BC_r^2 + \sum_{i \neq j} \mathbb{E} \left\langle \nabla_{\alpha_k^t} r_{\alpha_k^t}(s_i^E, a_i^E) - \mathbb{E}_{(s,a) \sim \nu_{\pi_E}} [\nabla_{\alpha_k^t} r_{\alpha_k^t}(s, a)], \nabla_{\alpha_k^t} r_{\alpha_k^t}(s_j^E, a_j^E) - \mathbb{E}_{(s,a) \sim \nu_{\pi_E}} [\nabla_{\alpha_k^t} r_{\alpha_k^t}(s, a)] \right\rangle \end{aligned} \tag{13}$$

Define the filtration $\mathcal{F}_i = \sigma(s_0^E, a_0^E, s_1^E, a_1^E, \dots, s_i^E, a_i^E)$. We continue to bound the second term in eq. (13) as follows:

$$\begin{aligned} & \mathbb{E} \left[\left\langle \nabla_{\alpha_k^t} r_{\alpha_k^t}(s_i^E, a_i^E) - \mathbb{E}_{(s,a) \sim \nu_{\pi_E}} [\nabla_{\alpha_k^t} r_{\alpha_k^t}(s, a)], \nabla_{\alpha_k^t} r_{\alpha_k^t}(s_j^E, a_j^E) - \mathbb{E}_{(s,a) \sim \nu_{\pi_E}} [\nabla_{\alpha_k^t} r_{\alpha_k^t}(s, a)] \right\rangle \right] \\ &= \mathbb{E} \left[\mathbb{E} \left[\left\langle \nabla_{\alpha_k^t} r_{\alpha_k^t}(s_i^E, a_i^E) - \mathbb{E}_{(s,a) \sim \nu_{\pi_E}} [\nabla_{\alpha_k^t} r_{\alpha_k^t}(s, a)], \nabla_{\alpha_k^t} r_{\alpha_k^t}(s_j^E, a_j^E) - \mathbb{E}_{(s,a) \sim \nu_{\pi_E}} [\nabla_{\alpha_k^t} r_{\alpha_k^t}(s, a)] \right\rangle \middle| \mathcal{F}_i \right] \right] \\ &= \mathbb{E} \left[\left\langle \nabla_{\alpha_k^t} r_{\alpha_k^t}(s_i^E, a_i^E) - \mathbb{E}_{(s,a) \sim \nu_{\pi_E}} [\nabla_{\alpha_k^t} r_{\alpha_k^t}(s, a)], \mathbb{E} [\nabla_{\alpha_k^t} r_{\alpha_k^t}(s_j^E, a_j^E) | \mathcal{F}_i] - \mathbb{E}_{(s,a) \sim \nu_{\pi_E}} [\nabla_{\alpha_k^t} r_{\alpha_k^t}(s, a)] \right\rangle \right] \\ &\leq \mathbb{E} \left[\left\| \nabla_{\alpha_k^t} r_{\alpha_k^t}(s_i^E, a_i^E) - \mathbb{E}_{(s,a) \sim \nu_{\pi_E}} [\nabla_{\alpha_k^t} r_{\alpha_k^t}(s, a)] \right\|_2 \left\| \mathbb{E} [\nabla_{\alpha_k^t} r_{\alpha_k^t}(s_j^E, a_j^E) | \mathcal{F}_i] - \mathbb{E}_{(s,a) \sim \nu_{\pi_E}} [\nabla_{\alpha_k^t} r_{\alpha_k^t}(s, a)] \right\|_2 \right] \\ &\leq 2C_r \mathbb{E} \left[\left\| \mathbb{E} [\nabla_{\alpha_k^t} r_{\alpha_k^t}(s_j^E, a_j^E) | \mathcal{F}_i] - \mathbb{E}_{(s,a) \sim \nu_{\pi_E}} [\nabla_{\alpha_k^t} r_{\alpha_k^t}(s, a)] \right\|_2 \right] \\ &= 2C_r \mathbb{E} \left\| \int_{s \sim \mathbb{P}(s_j \in \cdot | s_i^E, a_i^E), a \sim \pi_E(\cdot | s)} \nabla_{\alpha_k^t} r_{\alpha_k^t}(s, a) ds da - \int_{s \sim \chi_\theta, a \sim \pi_E(\cdot | s)} \nabla_{\alpha_k^t} r_{\alpha_k^t}(s, a) ds da \right\|_2 \\ &= 2C_r \mathbb{E} \sqrt{\sum_{l=1}^q \left(\int_{s \sim \mathbb{P}(s_j \in \cdot | s_i^E, a_i^E), a \sim \pi_E(\cdot | s)} \frac{\partial r_\alpha}{\partial \alpha_l} |_{\alpha=\alpha_k^t}(s, a) ds da - \int_{s \sim \chi_\theta, a \sim \pi_E(\cdot | s)} \frac{\partial r_\alpha}{\partial \alpha_l} |_{\alpha=\alpha_k^t}(s, a) ds da \right)^2} \end{aligned}$$

$$\stackrel{(i)}{\leq} 2C_r \mathbb{E} \sqrt{\sum_{l=1}^q \left(\left\| \frac{\partial r_\alpha}{\partial \alpha_i} \right\|_\infty d_{TV}(\mathbb{P}(s_j \in \cdot | s_i = s_i^E, a_i = a_i^E), \chi_{\pi_E} \pi_E) \right)^2}, \quad (14)$$

where (i) follows from the fact that $|\int f d\mu - \int f d\nu| \leq \|f\|_\infty d_{TV}(\mu, \nu)$. We next derive a bound on the total variation distance in the above equation as follows.

$$\begin{aligned} d_{TV}(\mathbb{P}(s_j \in \cdot, a_j \in \cdot | s_i = s_i^E, a_i = a_i^E), \chi_{\pi_E} \pi_E) &= d_{TV}(\mathbb{P}(s_j \in \cdot | s_i = s_i^E, a_i = a_i^E), \chi_{\pi_E}) \\ &= d_{TV}\left(\int_s \mathbb{P}(s_j \in \cdot | s_{i+1} = s) d\tilde{\mathbb{P}}(s | s_i = s_i^E, a_i = a_i^E), \chi_{\pi_E}\right) \\ &\leq \int_s d_{TV}(\mathbb{P}(s_j \in \cdot | s_{i+1} = s), \chi_{\pi_E}) d\tilde{\mathbb{P}}(s | s_i = s_i^E, a_i = a_i^E) \\ &\stackrel{(i)}{\leq} \int_s C_M \rho^{j-i-1} d\tilde{\mathbb{P}}(s | s_i = s_i^E, a_i = a_i^E) = C_M \rho^{j-i-1}, \end{aligned} \quad (15)$$

where (i) follows from Assumption 3. Substituting eq. (15) into eq. (14) and then further into eq. (13) yields the following upper-bound on T_1

$$T_1 \leq 4BC_r^2 + 2 \sum_{i=0}^{B-2} \sum_{j=i+1}^{B-1} 2C_M C_r^2 \rho^{j-i-1} \leq 4BC_r^2 \left(1 + \frac{C_M}{1-\rho}\right). \quad (16)$$

By following steps similar to those from eqs. (13) to (16), we can show that

$$T_2 \leq 4BC_r^2 \left(1 + \frac{C_M}{1-\rho}\right).$$

Therefore, we have

$$\mathbb{E} \left[\left\| \widehat{\nabla}_\alpha F(\theta_t, \alpha_k^t) - \nabla_\alpha F(\theta_t, \alpha_k^t) \right\|_2^2 \right] \leq \frac{16C_r^2}{(1-\gamma)^2} \left(1 + \frac{C_M}{1-\rho}\right) \frac{1}{B}.$$

□

Lemma 5. Suppose Assumptions 3 and 4 hold. Consider Algorithm 1 with α -update stepsize $\beta = \frac{\mu}{4L_{22}^2}$. For any $0 \leq t \leq T-1$, we have

$$\mathbb{E} \left[\left\| \alpha_K^t - \alpha_{op}(\theta_t) \right\|_2^2 \right] \leq C_\alpha^2 e^{-\frac{\mu^2}{8L_{22}^2} K} + \frac{48C_r^2}{\mu^2(1-\gamma)^2} \left(1 + \frac{C_M}{1-\rho}\right) \frac{1}{B}.$$

Let $K \geq \frac{8L_{22}^2}{\mu^2} \log \frac{2C_\alpha^2}{\Delta_\alpha}$ and $B \geq \frac{96C_r^2}{\mu^2(1-\gamma)^2} \left(1 + \frac{C_M}{1-\rho}\right) \frac{1}{\Delta_\alpha}$, we have $\mathbb{E} \left[\left\| \alpha_K^t - \alpha_{op}(\theta_t) \right\|_2^2 \right] \leq \Delta_\alpha$. The expected total computational complexity is given by

$$KB = \mathcal{O} \left(\frac{1}{(1-\gamma)^2 \Delta_\alpha} \log \left(\frac{1}{\Delta_\alpha} \right) \right).$$

Proof of Lemma 5. We proceed as follows:

$$\begin{aligned} \left\| \alpha_{k+1}^t - \alpha_{op}(\theta_t) \right\|_2^2 &\stackrel{(i)}{\leq} \left\| \alpha_k^t + \beta \widehat{\nabla}_\alpha F(\theta_t, \alpha_k^t) - \alpha_{op}(\theta_t) \right\|_2^2 \\ &= \left\| \alpha_k^t - \alpha_{op}(\theta_t) \right\|_2^2 + \beta^2 \left\| \widehat{\nabla}_\alpha F(\theta_t, \alpha_k^t) \right\|_2^2 + 2\beta \left\langle \widehat{\nabla}_\alpha F(\theta_t, \alpha_k^t), \alpha_k^t - \alpha_{op}(\theta_t) \right\rangle \\ &\stackrel{(ii)}{\leq} \left\| \alpha_k^t - \alpha_{op}(\theta_t) \right\|_2^2 + 2\beta^2 \left\| \nabla_\alpha F(\theta_t, \alpha_k^t) \right\|_2^2 + 2\beta^2 \left\| \widehat{\nabla}_\alpha F(\theta_t, \alpha_k^t) - \nabla_\alpha F(\theta_t, \alpha_k^t) \right\|_2^2 \\ &\quad + 2\beta \left\langle \nabla_\alpha F(\theta_t, \alpha_k^t), \alpha_k^t - \alpha_{op}(\theta_t) \right\rangle + 2\beta \left\langle \widehat{\nabla}_\alpha F(\theta_t, \alpha_k^t) - \nabla_\alpha F(\theta_t, \alpha_k^t), \alpha_k^t - \alpha_{op}(\theta_t) \right\rangle \\ &\stackrel{(iii)}{\leq} (1 - 2\beta\mu + 2\beta^2 L_{22}^2) \left\| \alpha_k^t - \alpha_{op}(\theta_t) \right\|_2^2 + 2\beta^2 \left\| \widehat{\nabla}_\alpha F(\theta_t, \alpha_k^t) - \nabla_\alpha F(\theta_t, \alpha_k^t) \right\|_2^2 \end{aligned}$$

$$\begin{aligned}
 & + 2\beta \left\langle \widehat{\nabla}_\alpha F(\theta_t, \alpha_k^t) - \nabla_\alpha F(\theta_t, \alpha_k^t), \alpha_k^t - \alpha_{op}(\theta_t) \right\rangle \\
 & \stackrel{(iv)}{\leq} (1 + 2\beta^2 L_{22}^2 - \mu\beta) \|\alpha_k^t - \alpha_{op}(\theta_t)\|_2^2 + (2\beta^2 + \beta/\mu) \|\widehat{\nabla}_\alpha F(\theta_t, \alpha_k^t) - \nabla_\alpha F(\theta_t, \alpha_k^t)\|_2^2 \\
 & \stackrel{(v)}{\leq} \left(1 - \frac{\mu^2}{8L_{22}^2}\right) \|\alpha_k^t - \alpha_{op}(\theta_t)\|_2^2 + \frac{3}{8L_{22}^2} \|\widehat{\nabla}_\alpha F(\theta_t, \alpha_k^t) - \nabla_\alpha F(\theta_t, \alpha_k^t)\|_2^2,
 \end{aligned} \tag{17}$$

where (i) follows from the non-expansive property of the projection operator, (ii) follows because $\|A + B\|_2^2 \leq 2\|A\|_2^2 + 2\|B\|_2^2$, (iii) follows from Proposition 1 and the fact $\langle \nabla_\alpha F(\theta_t, \alpha_k^t), \alpha_k^t - \alpha_{op}(\theta_t) \rangle \leq -\mu \|\alpha_k^t - \alpha_{op}(\theta_t)\|_2^2$, (iv) follows because

$$\langle \widehat{\nabla}_\alpha F(\theta_t, \alpha_k^t) - \nabla_\alpha F(\theta_t, \alpha_k^t), \alpha_k^t - \alpha_{op}(\theta_t) \rangle \leq \frac{\mu}{2} \|\alpha_k^t - \alpha_{op}(\theta_t)\|_2^2 + \frac{1}{2\mu} \|\widehat{\nabla}_\alpha F(\theta_t, \alpha_k^t) - \nabla_\alpha F(\theta_t, \alpha_k^t)\|_2^2,$$

and (v) follows by letting $\beta = \frac{\mu}{4L_{22}^2}$ and because $\mu \leq L_{22}$.

Applying eq. (17) recursively and using the fact $1 - x \leq e^{-x}$, we obtain

$$\|\alpha_K^t - \alpha_{op}(\theta_t)\|_2^2 \leq e^{-\frac{\mu^2}{8L_{22}^2}K} \|\alpha_0^t - \alpha_{op}(\theta_t)\|_2^2 + \frac{3}{8L_{22}^2} \sum_{k=0}^{K-1} \left(1 - \frac{\mu^2}{8L_{22}^2}\right)^{K-1-k} \|\widehat{\nabla}_\alpha F(\theta_t, \alpha_k^t) - \nabla_\alpha F(\theta_t, \alpha_k^t)\|_2^2.$$

Then, taking expectation on both sides of above inequality and applying Lemma 4 yield

$$\begin{aligned}
 \mathbb{E} \left[\|\alpha_K^t - \alpha_{op}(\theta_t)\|_2^2 \right] & \leq C_\alpha^2 e^{-\frac{\mu^2}{8L_{22}^2}K} + \frac{3}{8L_{22}^2} \sum_{k=0}^{K-1} \left(1 - \frac{\mu^2}{8L_{22}^2}\right)^{K-1-k} \frac{16C_r^2}{(1-\gamma)^2} (1 + \frac{C_M}{1-\rho}) \frac{1}{B} \\
 & \leq C_\alpha^2 e^{-\frac{\mu^2}{8L_{22}^2}K} + \frac{48C_r^2}{\mu^2(1-\gamma)^2} (1 + \frac{C_M}{1-\rho}) \frac{1}{B},
 \end{aligned}$$

which completes the proof. \square

E Proof of Theorems 1 and 2: Global Convergence of PPG-GAIL and FWPG-GAIL

In this section, we provide the proof of Theorems 1 and 2. We first provide three supporting lemmas. Specifically, Lemmas 6 and 7 establish the smoothness condition of the global optimal $\alpha_{op}(\theta)$ and the gradient $\nabla g(\theta)$. Similar property has also been established in Nouiehed et al. (2019); Lin et al. (2020). Lemma 8 provides the upper bound on the bias and variance errors introduced by the stochastic gradient estimator of $\nabla_\theta F(\theta_t, \alpha_t)$.

E.1 Supporting Lemmas

Lemma 6. Suppose Assumptions 1 to 4 holds and the policy takes the direct parameterization specified in Section 2.2. We have $\|\alpha_{op}(\theta_1) - \alpha_{op}(\theta_2)\|_2 \leq \frac{L_{21}}{\mu} \|\theta_1 - \theta_2\|_2$, where $\alpha_{op}(\theta)$ is the unique global optimal that satisfies $\alpha_{op}(\theta) = \operatorname{argmax}_{\alpha \in \Lambda} F(\theta, \alpha)$.

Proof of Lemma 6. Since $F(\theta_1, \alpha)$ is strongly concave on α , the following two inequalities hold for all $\alpha \in \Lambda$,

$$F(\theta_1, \alpha_{op}(\theta_1)) - F(\theta_1, \alpha) \geq \frac{\mu}{2} \|\alpha - \alpha_{op}(\theta_1)\|_2^2, \tag{18}$$

$$F(\theta_1, \alpha_{op}(\theta_1)) - F(\theta_1, \alpha) \leq \frac{\|\nabla_\alpha F(\theta_1, \alpha)\|_2^2}{2\mu}. \tag{19}$$

In eqs. (18) and (19), letting $\alpha = \alpha_{op}(\theta_2)$ and using the gradient Lipschitz condition established in Proposition 1, we have

$$\frac{\mu}{2} \|\alpha_{op}(\theta_2) - \alpha_{op}(\theta_1)\|_2^2 \leq \frac{\|\nabla_\alpha F(\theta_1, \alpha_{op}(\theta_2))\|_2^2}{2\mu} \leq \frac{L_{21}^2 \|\theta_2 - \theta_1\|_2^2}{2\mu},$$

which implies $\|\alpha_{op}(\theta_1) - \alpha_{op}(\theta_2)\|_2 \leq \frac{L_{21}}{\mu} \|\theta_1 - \theta_2\|_2$. \square

Lemma 7. Suppose Assumptions 1 to 4 hold and the policy takes the direct parameterization specified in Section 2.2. Then we have

$$\nabla_{\theta}g(\theta) = \nabla_{\theta}F(\theta, \alpha)|_{\alpha=\alpha_{op}(\theta)},$$

and for any $\theta_1, \theta_2 \in \Theta_p$,

$$\|\nabla_{\theta}g(\theta_1) - \nabla_{\theta}g(\theta_2)\|_2 \leq (L_{11} + (L_{12}L_{21})/\mu) \|\theta_1 - \theta_2\|_2,$$

where L_{11} , L_{12} and L_{21} are defined in Proposition 1.

Proof of Lemma 7. Taking the directional derivative of $g(\theta)$ with respect to the direction ℓ , we have

$$\begin{aligned} \frac{\partial g(\theta)}{\partial \ell} &= \lim_{\epsilon \rightarrow 0} \frac{g(\theta + \epsilon\ell) - g(\theta)}{\epsilon} = \lim_{\epsilon \rightarrow 0} \frac{F(\theta + \epsilon\ell, \alpha_{op}(\theta + \epsilon\ell)) - F(\theta, \alpha_{op}(\theta))}{\epsilon} \\ &= \lim_{\epsilon \rightarrow 0} \frac{F(\theta + \epsilon\ell, \alpha_{op}(\theta + \epsilon\ell)) - F(\theta + \epsilon\ell, \alpha_{op}(\theta)) + F(\theta + \epsilon\ell, \alpha_{op}(\theta)) - F(\theta, \alpha_{op}(\theta))}{\epsilon} \\ &\stackrel{(i)}{=} \lim_{\epsilon \rightarrow 0} \ell^{\top} \nabla_{\alpha} F(\theta, \alpha'_{\epsilon}) + \ell^{\top} \nabla_{\theta} F(\theta, \alpha_{op}(\theta)) \\ &\stackrel{(ii)}{=} \ell^{\top} \nabla_{\theta} F(\theta, \alpha_{op}(\theta)), \end{aligned} \tag{20}$$

where α'_{ϵ} in (i) is a point between $\alpha_{op}(\theta + \epsilon\ell)$ and $\alpha_{op}(\theta)$, and (ii) follows from Lemma 6 and hence we have $\lim_{\epsilon \rightarrow 0} \nabla_{\alpha} F(\theta, \alpha'_{\epsilon}) = \nabla_{\alpha} F(\theta, \alpha_{op}(\theta)) = 0$. Since eq. (20) holds for all directions ℓ , we have $\nabla_{\theta}g(\theta) = \nabla_{\theta}F(\theta, \alpha_{op}(\theta))$.

We then proceed to prove the gradient Lipschitz condition of $g(\theta_t)$. For any given $\theta_1, \theta_2 \in \Theta_p$, we have

$$\begin{aligned} \|\nabla_{\theta}g(\theta_1) - \nabla_{\theta}g(\theta_2)\|_2 &= \|\nabla_{\theta}F(\theta_1, \alpha_{op}(\theta_1)) - \nabla_{\theta}F(\theta_2, \alpha_{op}(\theta_2))\|_2 \\ &= \|\nabla_{\theta}F(\theta_1, \alpha_{op}(\theta_1)) - \nabla_{\theta}F(\theta_1, \alpha_{op}(\theta_2)) + \nabla_{\theta}F(\theta_1, \alpha_{op}(\theta_2)) - \nabla_{\theta}F(\theta_2, \alpha_{op}(\theta_2))\|_2 \\ &\leq \|\nabla_{\theta}F(\theta_1, \alpha_{op}(\theta_1)) - \nabla_{\theta}F(\theta_1, \alpha_{op}(\theta_2))\|_2 + \|\nabla_{\theta}F(\theta_1, \alpha_{op}(\theta_2)) - \nabla_{\theta}F(\theta_2, \alpha_{op}(\theta_2))\|_2 \\ &\leq L_{12} \|\alpha_{op}(\theta_1) - \alpha_{op}(\theta_2)\|_2 + L_{11} \|\theta_1 - \theta_2\|_2 \\ &\stackrel{(i)}{\leq} (L_{11} + \frac{L_{12}L_{21}}{\mu}) \|\theta_1 - \theta_2\|_2, \end{aligned}$$

where (i) follows from Lemma 6. \square

Lemma 8. Suppose Assumption 3 holds. For the policy gradient estimation specified in eq. (3), in each iteration t , $0 \leq t \leq T-1$, we have

$$\mathbb{E} \left[\left\| \hat{\nabla}_{\theta}F(\theta_t, \alpha_t) - \nabla_{\theta}F(\theta_t, \alpha_t) \right\|_2^2 \right] \leq \frac{4|\mathcal{A}|R_{max}^2}{(1-\gamma^{1/2})^2(1-\gamma)^2} \left(1 + \frac{2C_M\rho}{1-\rho} \right) \frac{1}{b}.$$

Let the sample trajectory size $b \geq \frac{4|\mathcal{A}|R_{max}^2}{(1-\gamma^{1/2})^2(1-\gamma)^2} \left(1 + \frac{2C_M\rho}{1-\rho} \right) \frac{1}{\Delta_{\theta}}$, we have $\mathbb{E} \left[\left\| \hat{\nabla}_{\theta}F(\theta_t, \alpha_t) - \nabla_{\theta}F(\theta_t, \alpha_t) \right\|_2^2 \right] \leq \Delta_{\theta}$.

Proof of Lemma 8. We define the vector $g_i \in \mathbb{R}^{|\mathcal{S}|\cdot|\mathcal{A}|}$ with each entry given by $(g_i)_{s,a} = -\frac{\hat{Q}(s,a)}{1-\gamma} \mathbb{1}\{s_i = s\}$. Then, we proceed as follows:

$$\begin{aligned} \mathbb{E} \left[\left\| \hat{\nabla}_{\theta}F(\theta_t, \alpha_t) - \nabla_{\theta}F(\theta_t, \alpha_t) \right\|_2^2 \right] &= \mathbb{E} \left[\left\| \frac{1}{b} \sum_{i=0}^{b-1} (g_i - \nabla_{\theta}F(\theta_t, \alpha_t)) \right\|_2^2 \right] \\ &= \frac{1}{b^2} \mathbb{E} \left[\sum_{i=0}^{b-1} \mathbb{E} \|g_i - \nabla_{\theta}F(\theta_t, \alpha_t)\|_2^2 + \sum_{i \neq j} \mathbb{E} \langle g_i - \nabla_{\theta}F(\theta_t, \alpha_t), g_j - \nabla_{\theta}F(\theta_t, \alpha_t) \rangle \right] \\ &\stackrel{(i)}{\leq} \frac{4|\mathcal{A}|R_{max}^2}{b(1-\gamma^{1/2})^2(1-\gamma)^2} + \frac{2}{b^2} \sum_{i=1}^{b-2} \sum_{j=i+1}^{b-1} \underbrace{\mathbb{E} [\langle g_i - \nabla_{\theta}F(\theta_t, \alpha_t), g_j - \nabla_{\theta}F(\theta_t, \alpha_t) \rangle]}_{T_1}, \end{aligned} \tag{21}$$

where (i) follows from the facts that $\|g_i\|_2 = \left\| \frac{\sqrt{|\mathcal{A}|} \hat{Q}(s_i, a_i)}{1-\gamma} \right\| \leq \frac{\sqrt{|\mathcal{A}|} R_{max}}{(1-\gamma^{1/2})(1-\gamma)}$ and $\|\nabla_\theta F(\theta_t, \alpha_t)\|_2 \leq \frac{\sqrt{|\mathcal{A}|} R_{max}}{(1-\gamma)^2} \leq \frac{\sqrt{|\mathcal{A}|} R_{max}}{(1-\gamma^{1/2})(1-\gamma)}$.

Define the filtration $\mathcal{F}_i = \sigma(s_0, s_1, \dots, s_i)$. For the term T_1 in eq. (21) with $i < j$, we have

$$\begin{aligned}
 \mathbb{E}[\langle g_i - \nabla_\theta F(\theta_t, \alpha_t), g_j - \nabla_\theta F(\theta_t, \alpha_t) \rangle] &= \mathbb{E}[\mathbb{E}[\langle g_i - \nabla_\theta F(\theta_t, \alpha_t), g_j - \nabla_\theta F(\theta_t, \alpha_t) \rangle | \mathcal{F}_i]] \\
 &= \mathbb{E}[\langle g_i - \nabla_\theta F(\theta_t, \alpha_t), \mathbb{E}[g_j - \nabla_\theta F(\theta_t, \alpha_t) | \mathcal{F}_i] \rangle] \\
 &\leq \mathbb{E}[\|g_i - \nabla_\theta F(\theta_t, \alpha_t)\|_2 \|\mathbb{E}[g_j - \nabla_\theta F(\theta_t, \alpha_t) | \mathcal{F}_i]\|_2] \\
 &\leq \frac{2R_{max}\sqrt{|\mathcal{A}|}}{(1-\gamma)(1-\gamma^{1/2})} \mathbb{E}\|\mathbb{E}[g_j | \mathcal{F}_i] - \nabla_\theta F(\theta_t, \alpha_t)\|_2 \\
 &\leq \frac{2R_{max}\sqrt{|\mathcal{A}|}}{(1-\gamma)(1-\gamma^{1/2})} \mathbb{E}\left\| \sqrt{\sum_{s,a} \left(\mathbb{P}\{s_j = s | s_i\} \frac{Q(s,a)}{1-\gamma} - d_{\pi_{\theta_t}}(s) \frac{Q(s,a)}{1-\gamma} \right)^2} \right\|_2 \\
 &\leq \frac{2R_{max}^2\sqrt{|\mathcal{A}|}}{(1-\gamma)^3(1-\gamma^{1/2})} \sqrt{\sum_{s,a} (\mathbb{P}\{s_j = s | s_i\} - d_{\pi_{\theta_t}}(s))^2} \\
 &\stackrel{(i)}{=} \frac{2R_{max}^2|\mathcal{A}|}{(1-\gamma)^3(1-\gamma^{1/2})} \|\mathbb{P}\{s_j = \cdot | s_i\} - \chi_{\pi_{\theta_t}}\|_2 \\
 &\stackrel{(ii)}{\leq} \frac{4C_M R_{max}^2 |\mathcal{A}|}{(1-\gamma)^3(1-\gamma^{1/2})} \rho^{j-i}, \tag{22}
 \end{aligned}$$

where (i) follows because $\chi_{\pi_{\theta_t}} = d_{\pi_{\theta_t}}$, and (ii) follows from Assumption 3 and because $d_{\pi_{\theta_t}} = \chi_{\theta_t}$ and

$$\|\mathbb{P}\{s_j = \cdot | s_i\} - d_{\pi_{\theta_t}}\|_2 \leq \|\mathbb{P}\{s_j = \cdot | s_i\} - d_{\pi_{\theta_t}}\|_1 = 2d_{TV}(\mathbb{P}\{s_j = \cdot | s_i\}, d_{\pi_{\theta_t}}).$$

Substituting eq. (22) into eq. (21), we obtain

$$\begin{aligned}
 \mathbb{E}\left[\left\|\widehat{\nabla}_\theta F(\theta_t, \alpha_t) - \nabla_\theta F(\theta_t, \alpha_t)\right\|_2^2\right] &\leq \frac{4|\mathcal{A}| R_{max}^2}{b(1-\gamma^{1/2})^2(1-\gamma)^2} + \frac{2}{b^2} \sum_{i=1}^{b-2} \sum_{j=i+1}^{b-1} \frac{4C_M |\mathcal{A}| R_{max}^2}{(1-\gamma^{1/2})^2(1-\gamma)^2} \rho^{j-i} \\
 &\leq \frac{4|\mathcal{A}| R_{max}^2}{b(1-\gamma^{1/2})^2(1-\gamma)^2} \left(1 + \frac{2C_M \rho}{1-\rho}\right) \frac{1}{b}.
 \end{aligned}$$

The second claim can be easily checked. \square

E.2 Proof of Theorem 1

Based on the projection property, we have

$$\langle \theta_t - \eta \widehat{\nabla}_\theta F(\theta_t, \alpha_t) - \theta_{t+1}, \theta - \theta_{t+1} \rangle \leq 0, \quad \forall \theta \in \Theta. \tag{23}$$

Next we use eq. (23) to upper bound on $\mathbb{E}[\|\theta_{t+1} - \theta_t\|_2^2]$. Letting $\theta = \theta_t$ and rearranging eq. (23) yield

$$\langle \widehat{\nabla}_\theta F(\theta_t, \alpha_t), \theta_{t+1} - \theta_t \rangle \leq -\eta^{-1} \|\theta_{t+1} - \theta_t\|_2^2. \tag{24}$$

According to the gradient Lipschitz condition established in Lemma 7, we have

$$\begin{aligned}
 g(\theta_{t+1}) &\leq g(\theta_t) + \langle \nabla_\theta g(\theta_t), \theta_{t+1} - \theta_t \rangle + \left(\frac{L_{11}}{2} + \frac{L_{12}L_{21}}{2\mu} \right) \|\theta_{t+1} - \theta_t\|_2^2 \\
 &= g(\theta_t) + \langle \widehat{\nabla}_\theta F(\theta_t, \alpha_t), \theta_{t+1} - \theta_t \rangle - \langle \nabla_\theta F(\theta_t, \alpha_t) - \nabla_\theta g(\theta_t), \theta_{t+1} - \theta_t \rangle
 \end{aligned}$$

$$\begin{aligned}
 & - \left\langle \widehat{\nabla}_\theta F(\theta_t, \alpha_t) - \nabla_\theta F(\theta_t, \alpha_t), \theta_{t+1} - \theta_t \right\rangle + \left(\frac{L_{11}}{2} + \frac{L_{12}L_{21}}{2\mu} \right) \|\theta_{t+1} - \theta_t\|_2^2 \\
 & \stackrel{(i)}{\leq} g(\theta_t) - \left(\frac{L_{11}}{2} + \frac{L_{12}L_{21}}{2\mu} \right) \|\theta_{t+1} - \theta_t\|_2^2 - \langle \nabla_\theta F(\theta_t, \alpha_t) - \nabla_\theta g(\theta_t), \theta_{t+1} - \theta_t \rangle \\
 & \quad - \left\langle \widehat{\nabla}_\theta F(\theta_t, \alpha_t) - \nabla_\theta F(\theta_t, \alpha_t), \theta_{t+1} - \theta_t \right\rangle,
 \end{aligned}$$

where (i) follows from eq. (24) and the fact that $\eta = \left(L_{11} + \frac{L_{12}L_{21}}{\mu} \right)^{-1}$.

Rearranging the above inequality, we obtain

$$\begin{aligned}
 \|\theta_{t+1} - \theta_t\|_2^2 & \leq \left(\frac{L_{11}}{2} + \frac{L_{12}L_{21}}{2\mu} \right)^{-1} (g(\theta_t) - g(\theta_{t+1})) \\
 & \quad - \left(\frac{L_{11}}{2} + \frac{L_{12}L_{21}}{2\mu} \right)^{-1} \langle \nabla_\theta F(\theta_t, \alpha_t) - \nabla_\theta g(\theta_t), \theta_{t+1} - \theta_t \rangle \\
 & \quad - \left(\frac{L_{11}}{2} + \frac{L_{12}L_{21}}{2\mu} \right)^{-1} \left\langle \widehat{\nabla}_\theta F(\theta_t, \alpha_t) - \nabla_\theta F(\theta_t, \alpha_t), \theta_{t+1} - \theta_t \right\rangle \\
 & \stackrel{(i)}{\leq} \left(\frac{L_{11}}{2} + \frac{L_{12}L_{21}}{2\mu} \right)^{-1} (g(\theta_t) - g(\theta_{t+1})) \\
 & \quad + \left(\frac{L_{11}}{2} + \frac{L_{12}L_{21}}{2\mu} \right)^{-2} \|\nabla_\theta F(\theta_t, \alpha_t) - \nabla_\theta g(\theta_t)\|_2^2 + \frac{1}{4} \|\theta_{t+1} - \theta_t\|_2^2 \\
 & \quad + \left(\frac{L_{11}}{2} + \frac{L_{12}L_{21}}{2\mu} \right)^{-2} \|\widehat{\nabla}_\theta F(\theta_t, \alpha_t) - \nabla_\theta F(\theta_t, \alpha_t)\|_2^2 + \frac{1}{4} \|\theta_{t+1} - \theta_t\|_2^2,
 \end{aligned}$$

where (i) follows from Young's inequality.

Taking expectation on both sides of the above inequality yields

$$\begin{aligned}
 \mathbb{E} [\|\theta_{t+1} - \theta_t\|_2^2] & \stackrel{(i)}{\leq} \frac{4\mu}{\mu L_{11} + L_{12}L_{21}} \mathbb{E} [g(\theta_t) - g(\theta_{t+1})] + \frac{8\mu^2 L_{22}^2}{(\mu L_{11} + L_{12}L_{21})^2} \mathbb{E} [\|\alpha_t - \alpha_{op}(\theta_t)\|_2^2] \\
 & \quad + \frac{8\mu^2}{(\mu L_{11} + L_{12}L_{21})^2} \mathbb{E} \left[\left\| \widehat{\nabla}_\theta F(\theta_t, \alpha_t) - \nabla_\theta F(\theta_t, \alpha_t) \right\|_2^2 \right], \tag{25}
 \end{aligned}$$

where (i) follows from the gradient Lipschitz condition established in Proposition 1

Next, rearranging eq. (23), we obtain

$$\begin{aligned}
 \langle \theta_t - \theta_{t+1}, \theta - \theta_{t+1} \rangle & \leq \eta \left\langle \widehat{\nabla}_\theta F(\theta_t, \alpha_t), \theta - \theta_{t+1} \right\rangle \\
 & = \eta \left\langle \widehat{\nabla}_\theta F(\theta_t, \alpha_t) - \nabla_\theta F(\theta_t, \alpha_t), \theta - \theta_{t+1} \right\rangle + \eta \langle \nabla_\theta F(\theta_t, \alpha_t) - \nabla_\theta g(\theta_t), \theta - \theta_{t+1} \rangle \\
 & \quad + \eta \langle \nabla_\theta g(\theta_t, \alpha_t), \theta - \theta_t \rangle + \eta \langle \nabla_\theta g(\theta_t, \alpha_t), \theta_t - \theta_{t+1} \rangle.
 \end{aligned}$$

Letting $\eta = \left(L_{11} + \frac{L_{12}L_{21}}{\mu} \right)^{-1}$ and rearranging the above inequality yield

$$\begin{aligned}
 \langle \nabla_\theta g(\theta_t), \theta - \theta_t \rangle & \geq \left(L_{11} + \frac{L_{12}L_{21}}{\mu} \right) \langle \theta_t - \theta_{t+1}, \theta - \theta_{t+1} \rangle - \langle \nabla_\theta F(\theta_t, \alpha_t) - \nabla_\theta g(\theta_t), \theta - \theta_{t+1} \rangle \\
 & \quad - \left\langle \widehat{\nabla}_\theta F(\theta_t, \alpha_t) - \nabla_\theta F(\theta_t, \alpha_t), \theta - \theta_{t+1} \right\rangle - \langle \nabla_\theta g(\theta_t), \theta_t - \theta_{t+1} \rangle \\
 & \stackrel{(i)}{\geq} - \left(L_{11} + \frac{L_{12}L_{21}}{\mu} \right) \|\theta_t - \theta_{t+1}\|_2 \cdot 2R - \frac{\sqrt{|\mathcal{A}|} R_{max}}{(1-\gamma)^2} \|\theta_{t+1} - \theta_t\|_2 \\
 & \quad - 2R (\|\widehat{\nabla}_\theta F(\theta_t, \alpha_t) - \nabla_\theta F(\theta_t, \alpha_t)\|_2 + \|\nabla_\theta F(\theta_t, \alpha_t) - \nabla_\theta g(\theta_t)\|_2), \tag{26}
 \end{aligned}$$

where (i) follows from the Cauchy-Schwartz inequality and the boundness properties of Θ_p ($R := \max_{\theta \in \Theta_p} \{\|\theta\|_2\}$) and because $\|\nabla_\theta g(\theta_t)\|_2 = \|\nabla_\theta F(\theta_t, \alpha_{op}(\theta_t))\|_2 \leq \frac{\sqrt{|\mathcal{A}|} R_{max}}{(1-\gamma)^2}$.

Applying the gradient dominance property of $g(\theta)$ established in Proposition 2, we obtain

$$\begin{aligned} g(\theta_t) - g(\theta^*) &\leq C_d \max_{\theta \in \Theta} \langle \nabla_\theta g(\theta_t), \theta_t - \theta \rangle \\ &\stackrel{(i)}{\leq} C_d \left(\frac{2(\mu L_{11} + L_{12}L_{21})R}{\mu} + \frac{\sqrt{|\mathcal{A}|}R_{max}}{(1-\gamma)^2} \right) \|\theta_t - \theta_{t+1}\|_2 \\ &\quad + 2RC_d \|\hat{\nabla}_\theta F(\theta_t, \alpha_t) - \nabla_\theta F(\theta_t, \alpha_t)\|_2 + 2RC_d \|\nabla_\theta F(\theta_t, \alpha_t) - \nabla_\theta g(\theta_t)\|_2, \end{aligned}$$

where (i) follows by multiplying -1 on both sides of eq. (26) and taking the maximum over all $\theta \in \Theta_p$.

Taking expectation on both sides of above inequality and telescoping, we have

$$\begin{aligned} &\frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[g(\theta_t)] - g(\theta^*) \\ &\leq C_d \left(\frac{2(\mu L_{11} + L_{12}L_{21})R}{\mu} + \frac{\sqrt{|\mathcal{A}|}R_{max}}{(1-\gamma)^2} \right) \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[\|\theta_t - \theta_{t+1}\|_2] \\ &\quad + 2RC_d \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[\|\hat{\nabla}_\theta F(\theta_t, \alpha_t) - \nabla_\theta F(\theta_t, \alpha_t)\|_2] + 2RC_d \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[\|\nabla_\theta F(\theta_t, \alpha_t) - \nabla_\theta g(\theta_t)\|_2] \\ &\stackrel{(i)}{\leq} C_d \left(\frac{2(\mu L_{11} + L_{12}L_{21})R}{\mu} + \frac{\sqrt{|\mathcal{A}|}R_{max}}{(1-\gamma)^2} \right) \sqrt{\mathbb{E}\left[\frac{1}{T} \sum_{t=0}^{T-1} \|\theta_t - \theta_{t+1}\|_2^2\right]} \\ &\quad + 2RC_d \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[\|\hat{\nabla}_\theta F(\theta_t, \alpha_t) - \nabla_\theta F(\theta_t, \alpha_t)\|_2] + 2RC_d \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[\|\nabla_\theta F(\theta_t, \alpha_t) - \nabla_\theta g(\theta_t)\|_2] \\ &\stackrel{(ii)}{\leq} \left(\frac{2(\mu L_{11} + L_{12}L_{21})R}{\mu} + \frac{\sqrt{|\mathcal{A}|}R_{max}}{(1-\gamma)^2} \right) C_d \sqrt{\frac{4\mu}{\mu L_{11} + L_{12}L_{21}} \frac{\mathbb{E}[g(\theta_0) - g(\theta_T)]}{T}} \\ &\quad + \left(\frac{2(\mu L_{11} + L_{12}L_{21})R}{\mu} + \frac{\sqrt{|\mathcal{A}|}R_{max}}{(1-\gamma)^2} \right) C_d \sqrt{\frac{8\mu^2 L_{22}^2}{(\mu L_{11} + L_{12}L_{21})^2} \mathbb{E}[\|\alpha_t - \alpha_{op}(\theta_t)\|_2^2]} \\ &\quad + \left(\frac{2(\mu L_{11} + L_{12}L_{21})R}{\mu} + \frac{\sqrt{|\mathcal{A}|}R_{max}}{(1-\gamma)^2} \right) C_d \sqrt{\frac{8\mu^2}{(\mu L_{11} + L_{12}L_{21})^2} \mathbb{E}[\|\hat{\nabla}_\theta F(\theta_t, \alpha_t) - \nabla_\theta F(\theta_t, \alpha_t)\|_2^2]} \\ &\quad + 2RC_d \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[\|\hat{\nabla}_\theta F(\theta_t, \alpha_t) - \nabla_\theta F(\theta_t, \alpha_t)\|_2] + 2RC_d \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[\|\nabla_\theta F(\theta_t, \alpha_t) - \nabla_\theta g(\theta_t)\|_2] \\ &\stackrel{(iii)}{\leq} \left(\frac{2(\mu L_{11} + L_{12}L_{21})R}{\mu} + \frac{\sqrt{|\mathcal{A}|}R_{max}}{(1-\gamma)^2} \right) C_d \sqrt{\frac{4\mu}{\mu L_{11} + L_{12}L_{21}} \frac{R_{max}}{(1-\gamma)T}} \\ &\quad + \left(\frac{\sqrt{|\mathcal{A}|}R_{max}}{(1-\gamma)^2} \frac{2\mu}{\mu L_{11} + L_{12}L_{21}} + 5R \right) 2L_{22} C_d \sqrt{C_\alpha^2 e^{-\frac{\mu^2}{8L_{22}^2} K} + \frac{48C_r^2}{\mu^2(1-\gamma)^2} (1 + \frac{C_M}{1-\rho}) \frac{1}{B}} \\ &\quad + \left(\frac{\sqrt{|\mathcal{A}|}R_{max}}{(1-\gamma)^2} \frac{2\mu}{\mu L_{11} + L_{12}L_{21}} + 5R \right) 2C_d \sqrt{\frac{4|\mathcal{A}|R_{max}^2}{b(1-\gamma^{1/2})^2(1-\gamma)^2} \left(1 + \frac{2C_M\rho}{1-\rho}\right) \frac{1}{b}} \\ &\stackrel{(iv)}{\leq} \mathcal{O}\left(\frac{1}{(1-\gamma)^3\sqrt{T}}\right) + \mathcal{O}\left(e^{-(1-\gamma)^2K}\right) + \mathcal{O}\left(\frac{1}{(1-\gamma)^3\sqrt{B}}\right) + \mathcal{O}\left(\frac{1}{(1-\gamma)^3\sqrt{b}}\right), \end{aligned}$$

where (i) follows because $\mathbb{E}[X] \leq \sqrt{\mathbb{E}[X^2]}$ holds for any random variable X , (ii) follows by telescoping eq. (25) and further because $\sqrt{a+b} \leq \sqrt{a} + \sqrt{b}$ holds, for all $a, b > 0$, (iii) follows from Lemmas 5 and 8 and because $\mathbb{E}[X] \leq \sqrt{\mathbb{E}[X^2]}$ holds for any random variable X , and (iv) follows because $L_{11} = \mathcal{O}\left(\frac{1}{(1-\gamma)^2}\right)$, $L_{12} = \mathcal{O}\left(\frac{1}{(1-\gamma)^2}\right)$, $L_{21} = \mathcal{O}\left(\frac{1}{1-\gamma}\right)$, $L_{22} = \mathcal{O}\left(\frac{1}{1-\gamma}\right)$, $C_d = \mathcal{O}\left(\frac{1}{1-\gamma}\right)$ and $\mathcal{O}\left(\frac{1}{1-\gamma^{1/2}}\right) \leq \mathcal{O}\left(\frac{1}{1-\gamma}\right)$.

E.3 Proof of Theorem 2

By the gradient Lipschitz condition (established in Lemma 7) of $g(\theta)$, we have

$$\begin{aligned}
 g(\theta_{t+1}) &\leq g(\theta_t) + \langle \nabla_\theta g(\theta_t), \theta_{t+1} - \theta_t \rangle + \left(\frac{L_{11}}{2} + \frac{L_{12}L_{21}}{2\mu} \right) \|\theta_{t+1} - \theta_t\|_2^2 \\
 &= g(\theta_t) + \eta \langle \nabla_\theta g(\theta_t), \hat{v}_t - \theta_t \rangle + \left(\frac{L_{11}}{2} + \frac{L_{12}L_{21}}{2\mu} \right) \eta^2 \|\hat{v}_t - \theta_t\|_2^2 \\
 &\stackrel{(i)}{\leq} g(\theta_t) + \eta \left\langle \widehat{\nabla}_\theta F(\theta_t, \alpha_t), \hat{v}_t - \theta_t \right\rangle + \eta \left\langle \nabla_\theta g(\theta_t) - \widehat{\nabla}_\theta F(\theta_t, \alpha_t), \hat{v}_t - \theta_t \right\rangle \\
 &\quad + \left(2L_{11} + \frac{2L_{12}L_{21}}{\mu} \right) \eta^2 R^2 \\
 &\stackrel{(ii)}{\leq} g(\theta_t) + \eta \left\langle \widehat{\nabla}_\theta F(\theta_t, \alpha_t), v_t - \theta_t \right\rangle + \eta \left\langle \nabla_\theta g(\theta_t) - \widehat{\nabla}_\theta F(\theta_t, \alpha_t), \hat{v}_t - \theta_t \right\rangle \\
 &\quad + \left(2L_{11} + \frac{2L_{12}L_{21}}{\mu} \right) \eta^2 R^2 \\
 &= g(\theta_t) + \eta \langle \nabla_\theta g(\theta_t), v_t - \theta_t \rangle + \eta \left\langle \nabla_\theta g(\theta_t) - \widehat{\nabla}_\theta F(\theta_t, \alpha_t), \hat{v}_t - v_t \right\rangle \\
 &\quad + \left(2L_{11} + \frac{2L_{12}L_{21}}{\mu} \right) \eta^2 R^2,
 \end{aligned} \tag{27}$$

where (i) follows because $\|\hat{v}_t - \theta_t\|_2 \leq 2R$, and (ii) follows by definition of \hat{v}_t in eq. (5) ($\hat{v}_t := \text{argmax}_{\theta \in \Theta_p} \langle \theta, -\widehat{\nabla}_\theta F(\theta_t, \alpha_t) \rangle$), and further we define $v_t := \text{argmax}_{\theta \in \Theta} \langle \theta, -\nabla_\theta g(\theta_t) \rangle$. We continue the proof as follows:

$$\begin{aligned}
 \max_{\theta \in \Theta} \langle \nabla_\theta g(\theta_t), \theta_t - \theta \rangle &\stackrel{(i)}{=} \langle \nabla_\theta g(\theta_t), \theta_t - v_t \rangle \\
 &\stackrel{(ii)}{\leq} \eta^{-1} (g(\theta_t) - g(\theta_{t+1})) + \left(2L_{11} + \frac{2L_{12}L_{21}}{\mu} \right) \eta R^2 \\
 &\quad + \langle \nabla_\theta g(\theta_t) - \nabla_\theta F(\theta_t, \alpha_t), \hat{v}_t - v_t \rangle + \left\langle \nabla_\theta F(\theta_t, \alpha_t) - \widehat{\nabla}_\theta F(\theta_t, \alpha_t), \hat{v}_t - v_t \right\rangle \\
 &\leq \eta^{-1} (g(\theta_t) - g(\theta_{t+1})) + \left(2L_{11} + \frac{2L_{12}L_{21}}{\mu} \right) \eta R^2 \\
 &\quad + 2R \|\nabla_\theta g(\theta_t) - \nabla_\theta F(\theta_t, \alpha_t)\|_2 + 2R \left\| \nabla_\theta F(\theta_t, \alpha_t) - \widehat{\nabla}_\theta F(\theta_t, \alpha_t) \right\|_2,
 \end{aligned} \tag{28}$$

where (i) follows by definition $v_t := \text{argmax}_{\theta \in \Theta} \langle \theta, -\nabla_\theta g(\theta_t) \rangle$, and (ii) follows by rearranging eq. (27).

Finally, we complete the proof as follows:

$$\begin{aligned}
 &\frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[g(\theta_t)] - g(\theta^*) \\
 &\stackrel{(i)}{\leq} C_d \cdot \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E} \left[\max_{\theta \in \Theta} \langle \nabla_\theta g(\theta_t), \theta_t - \theta \rangle \right] \\
 &\stackrel{(ii)}{\leq} \frac{C_d \mathbb{E}[g(\theta_0) - g(\theta_T)]}{\eta T} + C_d \left(2L_{11} + \frac{2L_{12}L_{21}}{\mu} \right) \eta R^2 + \frac{2RC_d}{T} \sum_{t=0}^{T-1} \mathbb{E} \|\nabla_\theta g(\theta_t) - \nabla_\theta F(\theta_t, \alpha_t)\|_2 \\
 &\quad + \frac{2RC_d}{T} \sum_{t=0}^{T-1} \mathbb{E} \left\| \nabla_\theta F(\theta_t, \alpha_t) - \widehat{\nabla}_\theta F(\theta_t, \alpha_t) \right\|_2 \\
 &\stackrel{(iii)}{\leq} C_d \cdot \frac{R_{\max} + 2(1-\gamma)^3 (L_{11} + L_{12}L_{21}\mu^{-1}) R^2}{(1-\gamma)^2 \sqrt{T}} + 2RC_d \sqrt{\frac{4|\mathcal{A}|R_{\max}^2}{b(1-\gamma^{1/2})^2(1-\gamma)^2} \left(1 + \frac{2C_M\rho}{1-\rho} \right) \frac{1}{b}} \\
 &\quad + 2RC_d L_{22} \sqrt{C_\alpha^2 e^{-\frac{\mu^2}{8L_{22}^2} K} + \frac{48C_r^2}{(1-\gamma)^2 \mu^2} \left(1 + \frac{C_M}{1-\rho} \right) \frac{1}{B}}
 \end{aligned}$$

$$\stackrel{(iv)}{\leq} \mathcal{O}\left(\frac{1}{(1-\gamma)^3\sqrt{T}}\right) + \mathcal{O}\left(e^{-(1-\gamma)^2K}\right) + \mathcal{O}\left(\frac{1}{(1-\gamma)^3\sqrt{B}}\right) + \mathcal{O}\left(\frac{1}{(1-\gamma)^3\sqrt{b}}\right),$$

where (i) follows from Proposition 2, (ii) follows from telescoping eq. (28), (iii) follows from Lemmas 5 and 8 and because $\eta = \frac{1-\gamma}{\sqrt{T}}$ and $\mathbb{E}[X] \leq \sqrt{\mathbb{E}[X^2]}$ holds for any random variable X , and (iv) follows because $L_{11} = \mathcal{O}\left(\frac{1}{(1-\gamma)^2}\right)$, $L_{12} = \mathcal{O}\left(\frac{1}{(1-\gamma)^2}\right)$, $L_{21} = \mathcal{O}\left(\frac{1}{1-\gamma}\right)$, $L_{22} = \mathcal{O}\left(\frac{1}{1-\gamma}\right)$, $C_d = \mathcal{O}\left(\frac{1}{1-\gamma}\right)$ and $\mathcal{O}\left(\frac{1}{1-\gamma^{1/2}}\right) \leq \mathcal{O}\left(\frac{1}{1-\gamma}\right)$.

F Proof of Theorems 3 and 4: Global Convergence of TRPO-GAIL

In this section, we add the subscript λ to the notations of the Q-function $Q_\alpha^\pi(s, a)$, the value function $V(\pi, r_\alpha)$, the objective function $F(\theta, \alpha)$ and $g(\theta)$ in order to emphasize that these functions are derived under λ -regularized MDP.

F.1 Supporting Lemmas

In this subsection, we introduce several useful lemmas.

Lemma 9. ((Beck, 2017, Lemma 9.1)) Consider a proper closed convex function $\omega: E \rightarrow (-\infty, \infty]$. Let $\text{dom}(\partial\omega)$ denote the subset of E where ω is differentiable and $\text{dom}(\omega)$ denote the subset of E where the value of ω is finite. Assume $a, b \in \text{dom}(\partial\omega)$ and $c \in \text{dom}(\omega)$. Then the following inequality holds:

$$\langle \nabla\omega(b) - \nabla\omega(a), c - a \rangle = B_\omega(c, a) + B_\omega(a, b) - B_\omega(c, b),$$

where $B_\omega(\cdot, \cdot)$ denotes the Bregman distance associated with $\omega(\cdot)$.

Lemma 10. ((Shani et al., 2020, Lemma 25)) Consider the Q-function estimation in Algorithm 3. For any $t \in \{0, 1, \dots, T-1\}$, we have

$$\left\| -\hat{Q}_{\lambda, \alpha_t}^{\pi_{\theta_t}}(s, \cdot) + \lambda \nabla\omega(\pi_{\theta_t}(\cdot|s)) \right\|_\infty \leq C_\omega(t; \lambda),$$

where $\hat{Q}_{\lambda, \alpha_t}^{\pi_{\theta_t}}$ is the Q-function estimated under the reward function r_{α_t} and policy π_{θ_t} , and $C_\omega(t; \lambda) \leq \mathcal{O}\left(\frac{C_r C_\alpha (1 + \sum_{\lambda \neq 0} \log t)}{1 - \gamma^{1/2}}\right)$.

Lemma 11. For any policy $\pi, \pi' \in \Delta_{\mathcal{A}}$ and $\alpha \in \Lambda$, the following equality holds,

$$(V_\lambda(\pi, r_\alpha) - V_\lambda(\pi', r_\alpha))(1 - \gamma) = \sum_{s \in \mathcal{S}} d_{\pi'}(s) (\langle -Q_{\lambda, \alpha}^\pi(s, \cdot) + \lambda \nabla\omega(\pi(\cdot|s)), \pi'(\cdot|s) - \pi(\cdot|s) \rangle + \lambda B_\omega(\pi'(\cdot|s), \pi(\cdot|s))),$$

where $V_\lambda(\pi, r_\alpha)$ is the average value function under λ -regularized MDP with the reward function r_α and $d_{\pi'}$ is the state visitation distribution of π' .

Proof of Lemma 11. Following from (Shani et al., 2020, Lemma 24), for any $s \in \mathcal{S}$, we have

$$\langle -Q_{\lambda, \alpha}^\pi(s, \cdot) + \lambda \nabla\omega(\pi(\cdot|s)), \pi'(\cdot|s) - \pi(\cdot|s) \rangle = -(T_\lambda^{\pi'} V_{\lambda, \alpha}^\pi(s) - V_{\lambda, \alpha}^\pi(s)) - \lambda B_\omega(\pi'(\cdot|s), \pi(\cdot|s)), \quad (29)$$

where $T_\lambda^{\pi'}$ is the Bellman operator under λ -regularized MDP, i.e.,

$$T_\lambda^{\pi'} V_{\lambda, \alpha}^\pi(s) = \sum_{a \in \mathcal{A}} (\pi'(a|s) r_{\alpha, \lambda}(s, a) + \sum_{s' \in \mathcal{S}} \mathsf{P}(s'|s, a) V_{\lambda, \alpha}^\pi(s')).$$

Furthermore, we have

$$\begin{aligned} V_\lambda(\pi', r_\alpha) - V_\lambda(\pi, r_\alpha) &= \sum_s \zeta(s) (V_{\lambda, \alpha}^{\pi'}(s) - V_{\lambda, \alpha}^\pi(s)) \\ &\stackrel{(i)}{=} \frac{1}{(1-\gamma)} \sum_{s \in \mathcal{S}} d_{\pi'}(s) (T_\lambda^{\pi'} V_{\lambda, \alpha}^\pi(s) - V_{\lambda, \alpha}^\pi(s)) \\ &\stackrel{(ii)}{=} -\frac{1}{1-\gamma} \sum_{s \in \mathcal{S}} d_{\pi'}(s) (\langle -Q_{\lambda, \alpha}^\pi(s, \cdot) + \lambda \nabla\omega(\pi(\cdot|s)), \pi'(\cdot|s) - \pi(\cdot|s) \rangle + \lambda B_\omega(\pi'(\cdot|s), \pi(\cdot|s))), \end{aligned}$$

where (i) follows from (Shani et al., 2020, Lemma 29) and (ii) follows by multiplying eq. (29) by $d_{\pi'}(s)$ and take the summation over \mathcal{S} . \square

F.2 Proof of Theorems 3 and 4

Since the unregularized MDP can be viewed as a special case of the regularized MDP, i.e., $\lambda = 0$, in this subsection, we first develop our proof for the general regularized MDP up to a certain step, and then specialize to the case with $\lambda = 0$ for proving Theorem 3 and continue to keep λ general for proving Theorem 4.

To we start the proof, recall that the update of θ_t specified in eq. (7) satisfies,

$$\pi_{\theta_{t+1}}(\cdot|s) \in \operatorname{argmin}_{\pi \in \Delta_{\mathcal{A}}} \underbrace{\left\langle -\hat{Q}_{\lambda, \alpha_t}^{\pi_{\theta_t}}(s, \cdot) + \lambda \nabla \omega(\pi_{\theta_t}(\cdot|s)), \pi - \pi_{\theta_t}(\cdot|s) \right\rangle + \eta_t^{-1} B_{\omega}(\pi, \pi_{\theta_t}(\cdot|s))}_{:= f_0(\pi)}.$$

Following from the first-order optimality condition, we have

$$\nabla_{\pi} f_0(\pi_{\theta_{t+1}}(\cdot|s))^{\top} (\pi - \pi_{\theta_{t+1}}(\cdot|s)) \geq 0, \forall \pi \in \Delta_{\mathcal{A}},$$

which together with the fact

$$\nabla_{\pi} f_0(\pi) = -\hat{Q}_{\lambda, \alpha_t}^{\pi_{\theta_t}}(s, \cdot) + \lambda \nabla \omega(\pi_{\theta_t}(\cdot|s)) + \eta_t^{-1} (\nabla \omega(\pi) - \nabla \omega(\pi_{\theta_t}(\cdot|s))),$$

implies that

$$\left\langle -\hat{Q}_{\lambda, \alpha_t}^{\pi_{\theta_t}}(s, \cdot) + \lambda \nabla \omega(\pi_{\theta_t}(\cdot|s)) + \eta_t^{-1} (\nabla \omega(\pi_{\theta_{t+1}}(\cdot|s)) - \nabla \omega(\pi_{\theta_t}(\cdot|s))), \pi - \pi_{\theta_{t+1}}(\cdot|s) \right\rangle \geq 0 \quad (30)$$

holds for any π .

Taking $\pi = \pi_{\theta^*}(\cdot|s)$ in eq. (30), we obtain

$$\begin{aligned} 0 &\leq \eta_t \left\langle -\hat{Q}_{\lambda, \alpha_t}^{\pi_{\theta_t}}(s, \cdot) + \lambda \nabla \omega(\pi_{\theta_t}(\cdot|s)), \pi_{\theta^*}(\cdot|s) - \pi_{\theta_t}(\cdot|s) \right\rangle \\ &\quad + \eta_t \left\langle -\hat{Q}_{\lambda, \alpha_t}^{\pi_{\theta_t}}(s, \cdot) + \lambda \nabla \omega(\pi_{\theta_t}(\cdot|s)), \pi_{\theta_t}(\cdot|s) - \pi_{\theta_{t+1}}(\cdot|s) \right\rangle \\ &\quad + \left\langle \nabla \omega(\pi_{\theta_{t+1}}(\cdot|s)) - \nabla \omega(\pi_{\theta_t}(\cdot|s)), \pi_{\theta^*}(\cdot|s) - \pi_{\theta_{t+1}}(\cdot|s) \right\rangle \\ &\stackrel{(i)}{\leq} \eta_t \left\langle -\hat{Q}_{\lambda, \alpha_t}^{\pi_{\theta_t}}(s, \cdot) + \lambda \nabla \omega(\pi_{\theta_t}(\cdot|s)), \pi_{\theta^*}(\cdot|s) - \pi_{\theta_t}(\cdot|s) \right\rangle \\ &\quad + \frac{\eta_t^2 \left\| -\hat{Q}_{\lambda, \alpha_t}^{\pi_{\theta_t}}(s, \cdot) + \lambda \nabla \omega(\pi_{\theta_t}(\cdot|s)) \right\|_{\infty}^2}{2} + \frac{\left\| \pi_{\theta_t}(\cdot|s) - \pi_{\theta_{t+1}}(\cdot|s) \right\|_1^2}{2} \\ &\quad + B_{\omega}(\pi_{\theta^*}(\cdot|s), \pi_{\theta_t}(\cdot|s)) - B_{\omega}(\pi_{\theta^*}(\cdot|s), \pi_{\theta_{t+1}}(\cdot|s)) - B_{\omega}(\pi_{\theta_{t+1}}(\cdot|s), \pi_{\theta_t}(\cdot|s)) \\ &\stackrel{(ii)}{\leq} \eta_t \left\langle -\hat{Q}_{\lambda, \alpha_t}^{\pi_{\theta_t}}(s, \cdot) + \lambda \nabla \omega(\pi_{\theta_t}(\cdot|s)), \pi_{\theta^*}(\cdot|s) - \pi_{\theta_t}(\cdot|s) \right\rangle + \frac{\eta_t^2 C_{\omega}(t; \lambda)^2}{2} \\ &\quad + B_{\omega}(\pi_{\theta^*}(\cdot|s), \pi_{\theta_t}(\cdot|s)) - B_{\omega}(\pi_{\theta^*}(\cdot|s), \pi_{\theta_{t+1}}(\cdot|s)), \end{aligned} \quad (31)$$

where (i) follows from Hölder's inequality and Lemma 9, and (ii) follows from the Lemma 10 and Pinsker's inequality given by

$$\frac{\left\| \pi_{\theta_t}(\cdot|s) - \pi_{\theta_{t+1}}(\cdot|s) \right\|_1^2}{2} \leq \text{KL}(\pi_{\theta_{t+1}}(\cdot|s) \| \pi_{\theta_t}(\cdot|s)) = B_{\omega}(\pi_{\theta_{t+1}}(\cdot|s), \pi_{\theta_t}(\cdot|s)),$$

where $\text{KL}(\cdot \| \cdot)$ denotes the KL-divergence.

Taking expectation conditioned on $\mathcal{F}_t = \sigma(\theta_0, \theta_1, \dots, \theta_t)$ over eq. (31), we have

$$\begin{aligned} 0 &\leq \eta_t \left\langle -Q_{\lambda, \alpha_t}^{\pi_{\theta_t}}(s, \cdot) + \lambda \nabla \omega(\pi_{\theta_t}(\cdot|s)), \pi_{\theta^*}(\cdot|s) - \pi_{\theta_t}(\cdot|s) \right\rangle + \frac{\eta_t^2 C_{\omega}(t; \lambda)^2}{2} \\ &\quad + B_{\omega}(\pi_{\theta^*}(\cdot|s), \pi_{\theta_t}(\cdot|s)) - \mathbb{E}[B_{\omega}(\pi_{\theta^*}(\cdot|s), \pi_{\theta_{t+1}}(\cdot|s)) | \mathcal{F}_t]. \end{aligned} \quad (32)$$

Since eq. (32) holds for any state, we multiply it by $d_{\pi_{\theta^*}}(s)$ for each state s and take the summation over \mathcal{S} . Then we rearrange the resulting bound and obtain

$$\frac{\eta_t^2 C_{\omega}(t; \lambda)^2}{2} + \sum_{s \in \mathcal{S}} d_{\pi_{\theta^*}}(s) B_{\omega}(\pi_{\theta^*}(\cdot|s), \pi_{\theta_t}(\cdot|s)) - \sum_{s \in \mathcal{S}} d_{\pi_{\theta^*}}(s) \mathbb{E}[B_{\omega}(\pi_{\theta^*}(\cdot|s), \pi_{\theta_{t+1}}(\cdot|s)) | \mathcal{F}_t]$$

$$\begin{aligned}
 & \geq -\eta_t \sum_{s \in \mathcal{S}} d_{\pi_{\theta^*}}(s) \left\langle -Q_{\lambda, \alpha_t}^{\pi_{\theta_t}}(s, \cdot) + \lambda \nabla \omega(\pi_{\theta_t}(\cdot|s)), \pi_{\theta^*}(\cdot|s) - \pi_{\theta_t}(\cdot|s) \right\rangle \\
 & \stackrel{(i)}{=} \eta_t(1-\gamma)(V_\lambda(\pi_{\theta^*}, r_{\alpha_t}) - V_\lambda(\pi_{\theta_t}, r_{\alpha_t})) + \eta_t \lambda \sum_{s \in \mathcal{S}} d_{\pi_{\theta^*}}(s) B_\omega(\pi_{\theta^*}(\cdot|s), \pi_{\theta_t}(\cdot|s)),
 \end{aligned} \tag{33}$$

where (i) follows from applying Lemma 11 with $\pi = \pi_{\theta_t}$ and $\pi' = \pi_{\theta^*}$. Rearranging eq. (33), we obtain

$$\begin{aligned}
 V_\lambda(\pi_{\theta^*}, r_{\alpha_t}) - V_\lambda(\pi_{\theta_t}, r_{\alpha_t}) & \leq \frac{1}{\eta_t(1-\gamma)} \sum_{s \in \mathcal{S}} d_{\pi_{\theta^*}}(s) (1 - \lambda \eta_t) \mathbb{E}[B_\omega(\pi_{\theta^*}(\cdot|s), \pi_{\theta_t}(\cdot|s))] \\
 & \quad - \frac{1}{\eta_t(1-\gamma)} \sum_{s \in \mathcal{S}} d_{\pi_{\theta^*}}(s) \mathbb{E}[B_\omega(\pi_{\theta^*}(\cdot|s), \pi_{\theta_{t+1}}(\cdot|s))] + \frac{\eta_t C_\omega(t, \lambda)^2}{2(1-\gamma)}.
 \end{aligned} \tag{34}$$

Furthermore, we proceed the proof as follows:

$$\begin{aligned}
 \mathbb{E}[g_\lambda(\theta_t)] - g_\lambda(\theta^*) & = \mathbb{E}[g_\lambda(\theta_t) - F_\lambda(\theta_t, \alpha_t)] + \mathbb{E}[F_\lambda(\theta_t, \alpha_t) - g_\lambda(\theta^*)] \\
 & \stackrel{(i)}{\leq} \mathbb{E}[g_\lambda(\theta_t) - F_\lambda(\theta_t, \alpha_t)] + \mathbb{E}[F_\lambda(\theta_t, \alpha_t) - F_\lambda(\theta^*, \alpha_t)] \\
 & \stackrel{(ii)}{=} \mathbb{E}[g_\lambda(\theta_t) - F_\lambda(\theta_t, \alpha_t)] + \mathbb{E}[V_\lambda(\pi_{\theta^*}, \alpha_t) - V_\lambda(\pi_{\theta_t}, \alpha_t)] \\
 & \stackrel{(iii)}{\leq} L_{22}^2 \mathbb{E}\left[\|\alpha_t - \alpha_{op}(\theta_t)\|_2^2\right] + \frac{1}{\eta_t(1-\gamma)} \sum_{s \in \mathcal{S}} d_{\pi_{\theta^*}}(s) (1 - \lambda \eta_t) \mathbb{E}[B_\omega(\pi_{\theta^*}(\cdot|s), \pi_{\theta_t}(\cdot|s))] \\
 & \quad - \frac{1}{\eta_t(1-\gamma)} \sum_{s \in \mathcal{S}} d_{\pi_{\theta^*}}(s) \mathbb{E}[B_\omega(\pi_{\theta^*}(\cdot|s), \pi_{\theta_{t+1}}(\cdot|s))] + \frac{\eta_t C_\omega(t, \lambda)^2}{2(1-\gamma)},
 \end{aligned} \tag{35}$$

where (i) follows because $g_\lambda(\theta^*) \geq F_\lambda(\theta^*, \alpha_{op}(\theta_t))$, (ii) follows from the definition of $F_\lambda(\theta, \alpha)$, and (iii) follows from the gradient Lipschitz condition of α in Proposition 1 and eq. (34).

Next, to prove Theorem 3, we let $\lambda = 0$ and recall $\eta_t = \frac{1-\gamma}{\sqrt{T}}$. Telescoping eq. (35), we obtain

$$\begin{aligned}
 \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[g(\theta_t)] - g(\theta^*) & \leq \frac{1}{(1-\gamma)^2 \sqrt{T}} \sum_{s \in \mathcal{S}} d_{\pi_{\theta^*}}(s) \mathbb{E}[B_\omega(\pi_{\theta^*}(\cdot|s), \pi_{\theta_0}(\cdot|s)) - B_\omega(\pi_{\theta^*}(\cdot|s), \pi_{\theta_T}(\cdot|s))] \\
 & \quad + \frac{L_{22}^2}{T} \sum_{t=0}^{T-1} \mathbb{E}\left[\|\alpha_t - \alpha_{op}(\theta_t)\|_2^2\right] + \frac{C_\omega^2}{2\sqrt{T}} \\
 & \stackrel{(i)}{\leq} L_{22}^2 C_\alpha^2 e^{-\frac{\mu^2}{8L_{22}^2} K} + \frac{48C_r^2 L_{22}^2}{\mu^2(1-\gamma)^2} \left(1 + \frac{C_M}{1-\rho}\right) \frac{1}{B} + \frac{(1-\gamma)^2 C_\omega^2 + 2 \log |\mathcal{A}|}{2(1-\gamma)^2 \sqrt{T}} \\
 & \stackrel{(ii)}{\leq} \mathcal{O}\left(\frac{1}{(1-\gamma)^2 \sqrt{T}}\right) + \mathcal{O}\left(e^{-(1-\gamma)^2 K}\right) + \mathcal{O}\left(\frac{1}{(1-\gamma)^4 B}\right),
 \end{aligned}$$

where (i) follows from Lemma 5 and because $0 \leq B_\omega(\pi_1, \pi_2) \leq \log |\mathcal{A}|$ for any θ_1, θ_2 and (ii) follows because $L_{22} = \mathcal{O}\left(\frac{1}{1-\gamma}\right)$ and $C_\omega = \mathcal{O}\left(\frac{1}{1-\gamma^{1/2}}\right) \leq \mathcal{O}\left(\frac{1}{1-\gamma}\right)$. This completes the proof of Theorem 3.

To prove the Theorem 4, let $\eta_t = \frac{1}{\lambda(t+2)}$. Then, telescoping eq. (35) and applying Lemma 5, we obtain

$$\begin{aligned}
 \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[g_\lambda(\theta_t)] - g_\lambda(\theta^*) & \leq L_{22}^2 C_\alpha^2 e^{-\frac{\mu^2}{8L_{22}^2} K} + \frac{48C_r^2 L_{22}^2}{\mu^2(1-\gamma)^2} \left(1 + \frac{C_M}{1-\rho}\right) \frac{1}{B} + \frac{C_\omega^2(T, \lambda)}{2(1-\gamma)\lambda} \frac{\log(T+1)}{T} \\
 & \quad + \frac{\lambda \sum_s d_{\pi_{\theta^*}(s)} \mathbb{E}[B_\omega(\pi_{\theta^*}(\cdot|s), \pi_{\theta_0}(\cdot|s)) - (T+1)B_\omega(\pi_{\theta^*}(\cdot|s), \pi_{\theta_T}(\cdot|s))]}{(1-\gamma)T} \\
 & \stackrel{(i)}{\leq} \mathcal{O}\left(\frac{1}{(1-\gamma)^3 T}\right) + \mathcal{O}\left(e^{-(1-\gamma)^2 K}\right) + \mathcal{O}\left(\frac{1}{(1-\gamma)^4 B}\right),
 \end{aligned}$$

where (i) follows because $0 \leq B_\omega(\pi_1, \pi_2) \leq \log(|\mathcal{A}|)$ for any π_1, π_2 , $L_{22} = \mathcal{O}\left(\frac{1}{1-\gamma}\right)$ and $C_\omega(T, \lambda) = \tilde{\mathcal{O}}\left(\frac{1}{1-\gamma^{1/2}}\right) \leq \tilde{\mathcal{O}}\left(\frac{1}{1-\gamma}\right)$. This completes the proof of Theorem 4.

G Proof of Theorem 5: Global Convergence of NPG-GAIL

To prove the theorem, we first define some notations. Let $\lambda_P := \min_{\theta \in \Theta} \{\lambda_{\min}(F(\theta) + \lambda I)\}$,

$$W_{\theta, \alpha}^{\lambda*} := (F(\theta) + \lambda I)^{-1} \mathbb{E}_{(s, a) \sim \nu_{\pi_\theta}} [A_\alpha^{\pi_\theta}(s, a) \nabla_\theta \log \pi_\theta(a|s)]$$

and

$$W_{\theta, \alpha}^* := F(\theta)^\dagger \mathbb{E}_{(s, a) \sim \nu_{\pi_\theta}} [A_\alpha^{\pi_\theta}(s, a) \nabla_\theta \log \pi_\theta(a|s)].$$

For brevity, we denote $W_t^{\lambda*} = W_{\theta_t, \alpha_t}^{\lambda*}$ and $W_t^* = W_{\theta_t, \alpha_t}^*$.

G.1 Supporting Lemmas

In this subsection, we give several useful lemmas.

Lemma 12. ((Agarwal et al., 2019, Lemma 3.2)) For any policy π and π' and reward function r_α , we have

$$V(\pi, r_\alpha) - V(\pi', r_\alpha) = \frac{1}{1-\gamma} \mathbb{E}_{s, a \sim \nu_\pi(s, a)} [A_\alpha^{\pi'}(s, a)].$$

Lemma 13. ((Xu et al., 2020a, Lemma 6)) For any θ and α , we have $\|W_{\theta, \alpha}^{\lambda*} - W_{\theta, \alpha}^*\|_2 \leq C_\lambda \lambda$, where $0 < C_\lambda < \infty$ is a constant only depending on the policy class.

Lemma 14. Suppose Assumptions 3 and 5 hold. Consider the policy update of NPG-GAIL (Algorithm 2) with $\beta_W = \frac{\lambda_P}{4(C_\phi^2 + \lambda)^2}$. Then, for all $t = 0, 1, \dots, T-1$, we have

$$\begin{aligned} \mathbb{E}[\|w_t - W_t^{\lambda*}\|_2^2] &\leq \exp \left\{ -\frac{\lambda_P^2 T_c}{16(C_\phi^2 + \lambda)^2} \right\} \frac{R_{\max}^2 C_\phi^2}{\lambda_P^2 (1-\gamma)^2} \\ &\quad + \left(\frac{1}{\lambda_P} + \frac{\lambda_P}{2(C_\phi^2 + \lambda)^2} \right) \frac{98 R_{\max}^2 C_\phi^2 [(C_\phi^2 + \lambda)^2 + 4\lambda_P^2][1 + (C_M - 1)\rho]}{(1-\rho)(1-\gamma)^2 \lambda_P^3 M}. \end{aligned}$$

Proof of Lemma 14. At iteration t , W_0, W_1, \dots, W_{T_c} follows the linear SA iteration rule defined in (Xu et al., 2020a, eq. (3)) with $\alpha = \beta_W$, $A = -(F(\theta_t) + \lambda I)$, $b = \mathbb{E}_{(s, a) \sim \nu_{\pi_{\theta_t}}} [A_{\alpha_t}^{\pi_{\theta_t}}(s, a) \nabla_{\theta_t} \log \pi_{\theta_t}(a|s)]$ and $\theta^* = -A^{-1}b = W_t^{\lambda*}$ with $\|W_t^{\lambda*}\|_2 \leq R_\theta = \frac{2C_\phi R_{\max}}{\lambda_A(1-\gamma)}$. It is easy to check that the Assumption 3 in Xu et al. (2020a) holds. Namely, (i), $\|A\|_F \leq C_\phi^2 + \lambda$ and $\|b\|_2 \leq \frac{2R_{\max}C_\phi}{1-\gamma}$; (ii), for any $w \in \mathbb{R}^d$, $\langle w - W_t^{\lambda*}, A(w - W_t^{\lambda*}) \rangle \leq -\lambda_p \|w - W_t^{\lambda*}\|_2^2$; (iii), The ergodicity of MDP is assumed here. Thus, applying (Xu et al., 2020a, Theorem 4) completes the proof. \square

G.2 Proof of Theorem 5

Define $D(\theta) = \mathbb{E}_{s \sim d_{\pi_{\theta^*}}} [\text{KL}(\pi_{\theta^*}(\cdot|s) \parallel \pi_\theta(\cdot|s))]$. Then we have

$$\begin{aligned} D(\theta_t) - D(\theta_{t+1}) &= \mathbb{E}_{\nu_{\pi_{\theta^*}}} [\log(\pi_{\theta_{t+1}}(\cdot|s)) - \log(\pi_{\theta_t}(\cdot|s))] \\ &\stackrel{(i)}{\geq} \mathbb{E}_{\nu_{\pi_{\theta^*}}} [\nabla_\theta \log(\pi_{\theta_t}(a|s))]^\top (\theta_{t+1} - \theta_t) - \frac{L_\phi^2}{2} \|\theta_{t+1} - \theta_t\|_2^2, \end{aligned}$$

where (i) follows from the gradient Lipschitz condition on $\log(\pi_\theta(\cdot|s))$ in Assumption 5.

Recall that the update rule in NPG-GAIL (Algorithm 2) is given by $\theta_{t+1} = \theta_t - \eta w_t$. Then we have

$$\begin{aligned} D(\theta_t) - D(\theta_{t+1}) &\geq \eta \mathbb{E}_{\nu_{\pi_{\theta^*}}} [\nabla_\theta \log(\pi_{\theta_t}(a|s))]^\top w_t - \frac{L_\phi^2 \eta^2}{2} \|w_t\|_2^2 \\ &= \eta \mathbb{E}_{\nu_{\pi_{\theta^*}}} [A_{\alpha_t}^{\pi_{\theta_t}}(s, a)] + \eta \mathbb{E}_{\nu_{\pi_{\theta^*}}} [\nabla_\theta \log(\pi_{\theta_t}(a|s))^\top W_t^* - A_{\alpha_t}^{\pi_{\theta_t}}(s, a)] \\ &\quad + \eta \mathbb{E}_{\nu_{\pi_{\theta^*}}} [\nabla_\theta \log(\pi_{\theta_t}(a|s))]^\top (W_t^{\lambda*} - W_t^*) + \eta \mathbb{E}_{\nu_{\pi_{\theta^*}}} [\nabla_\theta \log(\pi_{\theta_t}(a|s))]^\top (w_t - W_t^{\lambda*}) \\ &\quad - \frac{L_\phi^2 \eta^2}{2} \|w_t\|_2^2 \end{aligned}$$

$$\begin{aligned}
 &\stackrel{(i)}{=} (1-\gamma)\eta(V(\pi_{\theta^*}, r_{\alpha_t}) - V(\pi_{\theta_t}, r_{\alpha_t})) + \eta\mathbb{E}_{\nu_{\pi_{\theta^*}}} [\nabla_\theta \log(\pi_{\theta_t}(a|s))^\top W_t^* - A_{\alpha_t}^{\pi_{\theta_t}}(s, a)] \\
 &\quad + \eta\mathbb{E}_{\nu_{\pi_{\theta^*}}} [\nabla_\theta \log(\pi_{\theta_t}(a|s))]^\top (W_t^* - W_t) + \eta\mathbb{E}_{\nu_{\pi_{\theta^*}}} [\nabla_\theta \log(\pi_{\theta_t}(a|s))]^\top (w_t - W_t^*) \\
 &\quad - \frac{L_\phi^2\eta^2}{2} \|w_t\|_2^2 \\
 &\stackrel{(ii)}{\geq} (1-\gamma)\eta(V(\pi_{\theta^*}, r_{\alpha_t}) - V(\pi_{\theta_t}, r_{\alpha_t})) - \frac{L_\phi^2\eta^2}{2} \|w_t\|_2^2 \\
 &\quad + \eta\mathbb{E}_{\nu_{\pi_{\theta^*}}} [\nabla_\theta \log(\pi_{\theta_t}(a|s))]^\top (W_t^* - W_t) + \eta\mathbb{E}_{\nu_{\pi_{\theta^*}}} [\nabla_\theta \log(\pi_{\theta_t}(a|s))]^\top (w_t - W_t^*) \\
 &\quad - \eta\sqrt{\mathbb{E}_{\nu_{\pi_{\theta^*}}} [(\nabla_\theta \log(\pi_{\theta_t}(a|s))^\top W_t^* - A_{\alpha_t}^{\pi_{\theta_t}}(s, a))^2]} \\
 &\stackrel{(iii)}{\geq} (1-\gamma)\eta(V(\pi_{\theta^*}, r_{\alpha_t}) - V(\pi_{\theta_t}, r_{\alpha_t})) - \frac{L_\phi^2\eta^2}{2} \|w_t\|_2^2 \\
 &\quad + \eta\mathbb{E}_{\nu_{\pi_{\theta^*}}} [\nabla_\theta \log(\pi_{\theta_t}(a|s))]^\top (W_t^* - W_t) + \eta\mathbb{E}_{\nu_{\pi_{\theta^*}}} [\nabla_\theta \log(\pi_{\theta_t}(a|s))]^\top (w_t - W_t^*) \\
 &\quad - \eta\sqrt{C_d\mathbb{E}_{\nu_{\pi_{\theta_t}}} [(\nabla_\theta \log(\pi_{\theta_t}(a|s))^\top W_t^* - A_{\alpha_t}^{\pi_{\theta_t}}(s, a))^2]}, \tag{36}
 \end{aligned}$$

where (i) follows from Lemma 12, (ii) follows from the concavity of $f(x) = \sqrt{x}$ and Jensen's inequality, and (iii) follows from the fact that $(\nabla_\theta \log(\pi_{\theta_t}(a|s))^\top W_t^* - A_{\alpha_t}^{\pi_{\theta_t}}(s, a))^2 \geq 0$ and $\left\| \frac{\nu_{\pi_{\theta^*}}}{\nu_{\pi_{\theta_t}}} \right\|_\infty \leq \frac{1}{(1-\gamma)\min\{\zeta(s)\}} := C_d$.

Continuing to bound eq. (36), we have

$$\begin{aligned}
 D(\theta_t) - D(\theta_{t+1}) &\stackrel{(i)}{\geq} (1-\gamma)\eta(V(\pi_{\theta^*}, r_{\alpha_t}) - V(\pi_{\theta_t}, r_{\alpha_t})) - \frac{L_\phi^2\eta^2}{2} \|w_t\|_2^2 - \eta\sqrt{C_d}\zeta' \\
 &\quad + \eta\mathbb{E}_{\nu_{\pi_{\theta^*}}} [\nabla_\theta \log(\pi_{\theta_t}(a|s))]^\top (W_t^* - W_t) + \eta\mathbb{E}_{\nu_{\pi_E}} [\nabla_\theta \log(\pi_{\theta_t}(a|s))]^\top (w_t - W_t^*) \\
 &\stackrel{(ii)}{\geq} (1-\gamma)\eta(V(\pi_{\theta^*}, r_{\alpha_t}) - V(\pi_{\theta_t}, r_{\alpha_t})) - \eta\sqrt{C_d}\zeta' - \eta C_\phi C_\lambda \lambda \\
 &\quad - \eta C_\phi \|w_t - W_t^*\|_2 - \frac{L_\phi^2\eta^2}{2} \|w_t\|_2^2 \\
 &\stackrel{(iii)}{\geq} (1-\gamma)\eta(V(\pi_{\theta^*}, r_{\alpha_t}) - V(\pi_{\theta_t}, r_{\alpha_t})) - \eta\sqrt{C_d}\zeta' - \eta C_\phi C_\lambda \lambda \\
 &\quad - \eta C_\phi \|w_t - W_t^*\|_2 - L_\phi^2\eta^2 \|w_t - W_t^*\|_2^2 - L_\phi^2\eta^2 \|W_t^*\|_2^2 \\
 &\stackrel{(iv)}{\geq} (1-\gamma)\eta(V(\pi_{\theta^*}, r_{\alpha_t}) - V(\pi_{\theta_t}, r_{\alpha_t})) - \eta\sqrt{C_d}\zeta' - \eta C_\phi C_\lambda \lambda \\
 &\quad - \eta C_\phi \|w_t - W_t^*\|_2 - L_\phi^2\eta^2 \|w_t - W_t^*\|_2^2 - \frac{L_\phi^2\eta^2}{\lambda_P^2} \|\nabla_\theta V(\theta_t, r_{\alpha_t})\|_2^2, \tag{37}
 \end{aligned}$$

where (i) follows from the definition of ζ' in the statement of Theorem 5, (ii) follows from the upper bound on $\|\nabla_\theta \pi_\theta(a|s)\|_2$ in Assumption 5, Lemma 13 and Cauchy-Schwartz inequality, (iii) follows from the fact $\|A + B\|_2^2 \leq 2\|A\|_2^2 + 2\|B\|_2^2$, and (iv) follows from the definition of $W_t^{\lambda^*}$ and because $\lambda_P I \preceq F(\theta_t) + \lambda I$.

Rearranging eq. (37), we obtain

$$\begin{aligned}
 V(\pi_{\theta^*}, r_{\alpha_t}) - V(\pi_{\theta_t}, r_{\alpha_t}) &\leq \frac{D(\theta_t) - D(\theta_{t+1})}{\eta(1-\gamma)} + \frac{\sqrt{C_d}\zeta'}{1-\gamma} + \frac{C_\phi C_\lambda \lambda}{1-\gamma} + \frac{C_\phi}{1-\gamma} \|w_t - W_t^*\|_2 \\
 &\quad + \frac{L_\phi^2\eta}{1-\gamma} \|w_t - W_t^*\|_2^2 + \frac{L_\phi^2\eta}{\lambda_P^2(1-\gamma)} \|\nabla_\theta V(\theta_t, r_{\alpha_t})\|_2^2. \tag{38}
 \end{aligned}$$

Finally, we complete the proof as follows:

$$\begin{aligned}
 &\frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[g(\theta_t)] - g(\theta^*) \\
 &= \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[g(\theta_t) - F(\theta_t, \alpha_t)] + \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[F(\theta_t, \alpha_t) - g(\theta^*)]
 \end{aligned}$$

$$\begin{aligned}
 &\stackrel{(i)}{\leq} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[g(\theta_t) - F(\theta_t, \alpha_t)] + \frac{1}{T} \sum_{t=0}^{T-1} (F(\theta_t, \alpha_t) - F(\theta^*, \alpha_t)) \\
 &= \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[g(\theta_t) - F(\theta_t, \alpha_t)] + \frac{1}{T} \sum_{t=0}^{T-1} (V(\pi_{\theta^*}, r_{\alpha_t}) - V(\pi_{\theta_t}, r_{\alpha_t})) \\
 &\stackrel{(ii)}{\leq} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[g(\theta_t) - F(\theta_t, \alpha_t)] + \frac{D(\theta_0) - D(\theta_T)}{(1-\gamma)\eta T} + \frac{\sqrt{C_d}\zeta'}{1-\gamma} + \frac{C_\phi C_\lambda \lambda}{1-\gamma} \\
 &\quad + \frac{C_\phi}{(1-\gamma)T} \sum_{t=0}^{T-1} \|w_t - W_t^{\lambda*}\|_2 + \frac{L_\phi^2 \eta}{(1-\gamma)T} \sum_{t=0}^{T-1} \|w_t - W_t^{\lambda*}\|_2^2 + \frac{L_\phi^2 \eta R_{max}^2 C_\phi^2}{(1-\gamma)^3 \lambda_P^2} \\
 &\stackrel{(iii)}{\leq} L_{22}^2 C_\alpha^2 e^{-\frac{\mu^2}{8L_{22}^2} K} + \frac{48C_r^2 L_{22}^2}{\mu^2(1-\gamma)^2} (1 + \frac{\rho C_M}{1-\rho}) \frac{1}{B} + \frac{\mathbb{E}[D(\theta_0) - D(\theta_T)]}{(1-\gamma)^2 \sqrt{T}} + \frac{\sqrt{C_d}\zeta'}{1-\gamma} + \frac{C_\phi C_\lambda \lambda}{1-\gamma} \\
 &\quad + \frac{C_\phi}{(1-\gamma)T} \sum_{t=0}^{T-1} \|w_t - W_t^{\lambda*}\|_2 + \frac{L_\phi^2}{T^{3/2}} \sum_{t=0}^{T-1} \|w_t - W_t^{\lambda*}\|_2^2 + \frac{L_\phi^2 R_{max}^2 C_\phi^2}{(1-\gamma)^2 \lambda_P^2 \sqrt{T}} \\
 &\stackrel{(iv)}{\leq} L_{22}^2 C_\alpha^2 e^{-\frac{\mu^2}{8L_{22}^2} K} + \frac{48C_r^2 L_{22}^2}{\mu^2(1-\gamma)^2} (1 + \frac{\rho C_M}{1-\rho}) \frac{1}{B} + \frac{\mathbb{E}[D(\theta_0) - D(\theta_T)]}{(1-\gamma)^2 \sqrt{T}} + \frac{\sqrt{C_d}\zeta'}{1-\gamma} + \frac{C_\phi C_\lambda \lambda}{1-\gamma} \\
 &\quad + \frac{C_\phi}{(1-\gamma)} \sqrt{\exp\left\{-\frac{\lambda_P^2 T_c}{16(C_\phi^2 + \lambda)^2}\right\} \frac{R_{max}^2 C_\phi^2}{\lambda_P^2 (1-\gamma)^2} + \left(\frac{1}{\lambda_P} + \frac{\lambda_P}{2(C_\phi^2 + \lambda)^2}\right) \frac{98R_{max}^2 C_\phi^2 [(C_\phi^2 + \lambda)^2 + 4\lambda_P^2] [1 + (C_M - 1)\rho]}{(1-\rho)(1-\gamma)^2 \lambda_P^3 M}} \\
 &\quad + \frac{L_\phi^2}{\sqrt{T}} \left(\exp\left\{-\frac{\lambda_P^2 T_c}{16(C_\phi^2 + \lambda)^2}\right\} \frac{R_{max}^2 C_\phi^2}{\lambda_P^2 (1-\gamma)^2} + \left(\frac{1}{\lambda_P} + \frac{\lambda_P}{2(C_\phi^2 + \lambda)^2}\right) \frac{98R_{max}^2 C_\phi^2 [(C_\phi^2 + \lambda)^2 + 4\lambda_P^2] [1 + (C_M - 1)\rho]}{(1-\rho)(1-\gamma)^2 \lambda_P^3 M} \right) \\
 &\quad + \frac{L_\phi^2 R_{max}^2 C_\phi^2}{(1-\gamma)^2 \lambda_P^2 \sqrt{T}} \\
 &\stackrel{(v)}{\leq} \mathcal{O}\left(\frac{1}{(1-\gamma)^2 \sqrt{T}}\right) + \mathcal{O}\left(e^{-(1-\gamma)^2 K}\right) + \mathcal{O}\left(\frac{1}{(1-\gamma)^4 B}\right) \\
 &\quad + \mathcal{O}\left(\frac{\zeta'}{(1-\gamma)^{3/2}}\right) + \mathcal{O}\left(\frac{\lambda}{1-\gamma}\right) + \mathcal{O}(e^{-T_c}) + \mathcal{O}\left(\frac{1}{(1-\gamma)^2 \sqrt{M}}\right),
 \end{aligned}$$

where (i) follows because $g(\theta^*) = F(\theta^*, \alpha_{op}(\theta^*)) \geq F(\theta^*, \alpha_t)$ and (ii) follows from eq. (38) and because $\|\nabla_\theta V(\theta_t, \alpha_t)\|_2 \leq \frac{R_{max} C_\phi}{1-\gamma}$, (iii) follows from Proposition 1 and Lemma 5, and the fact $\eta = \frac{1-\gamma}{\sqrt{T}}$, (iv) follows from Lemma 14, and (v) follows because $L_{22} = \mathcal{O}\left(\frac{1}{1-\gamma}\right)$ and $C_d = \mathcal{O}\left(\frac{1}{1-\gamma}\right)$.