

## Nonlinear function approx' in RL

Structural conditions:

$Q^*$  realizable

$$Q^* \in \mathcal{F} / Q$$

local optimism

$$Q_h^*(s, a) \leq Q_h(s, a)$$

linear MDP - low rank enough & LVI-UCB works

P/R are linear

$$Q \leftarrow \underbrace{\text{linear + bonuses}}_{\text{linear}}$$

(linear) Bellman completeness.

$$Q \in \mathcal{F} \Rightarrow TQ \in \mathcal{F}$$

How to measure complexity of  $\mathcal{F}$  for RL?

finite-horizon MDP  $M = (S, A, P, R, \mu, H)$

Realizability  $Q_h^*(s, a) = \langle \theta_h^*, \phi(s, a) \rangle$  for linear  $\in \mathcal{I}$  for nonlinear

Bellman completeness (linear) For any  $\theta$ ,  $\exists \bar{\theta}$  s.t.  $\theta \equiv Q$   
 $(T\theta)(s, a) = \langle \bar{\theta}, \phi(s, a) \rangle$

Global optimistic regret decomposition If  $Q_1, \dots, Q_H$  s.t.

$$\Rightarrow E_{s_1} \max_a Q_i(s_1, a) \geq E_{s_1} \max_a Q_i^*(s_1, a) \quad (\text{earlier } Q \geq Q^* \text{ optmistic})$$

and  $\pi$  greedy wrt.  $Q_i$ , then

$$J(\pi^*) - J(\pi) \leq \sum_{h=1}^H E_{(s_h, a_h) \sim d_h^{\pi}} [Q_h(s_h, a_h) - (TQ_{h+1})(s_h, a_h)]$$

$Q \leq TQ + \text{conf}_h(s, a)$

$$\text{Proof: } J(\pi^*) - J(\pi) = E_{s_1} [\underbrace{Q_i^*(s_1, \pi^*(s_1)) - Q_i^*(s_1, \pi(s_1))}_{\max_a Q_i^*(s_1, a)}]$$

$$\stackrel{\text{by global opt}}{\leq} E_{s_1} (\max_a Q_i(s_1, a) - Q_i^*(s_1, \pi(s_1))) \quad (1)$$

$$\stackrel{\pi \text{ is greedy wrt } Q_i}{\leq} E_{(s_1, a_1) \sim d_1^{\pi}} [Q_i(s_1, a_1) - Q_i^*(s_1, \pi(s_1))]$$

$$= E_{(s_1, a_1) \sim d_1^{\pi}} \underbrace{[Q_i(s_1, a_1) - (TQ_2)(s_1, a_1)]}_{+ (TQ_2)(s_1, a_1) - Q_i^*(s_1, \pi(s_1))}$$

$$\begin{aligned}
 &= \text{first term} + \cancel{R(s_1, a_1)} + E_{s_2} \left[ \max_a Q_2(s_2, a_2) \right] \\
 &\quad - \cancel{Q_1 - TQ_2} - R(s_1, a_1) - E_{s_2} [Q_2^*(s_2, \pi(s_1))] \quad (2) \\
 &= \sum_{k=1}^H E \left[ Q_k - TQ_{k+1} \right]
 \end{aligned}$$

Main challenge: Show global optimality only assuming Bellman completeness.

[linear] Bellman completeness : For any  $\underline{\theta}, \bar{\theta}$  st.

$$+_{(S,a)} \quad (T\Theta)_{(S,a)} = \langle \bar{\Theta}, \phi|_{(S,a)} \rangle$$

$$E[R(s,a) + \max_{a'} Q(s',a')]$$

$$\langle \theta, \phi(s, a') \rangle$$

$\Rightarrow$  no misspecification in regression if take  $Q$  to be linear.

$$\textcircled{1} \quad \begin{aligned} \text{Regression error } f_h^i(\theta, \tilde{\theta}_{h+1}) &= \sum_{i=1}^{t-1} (\langle \phi(s_h^i, a_h^i), \theta \rangle - g_h^i - \max_a \langle \phi(s_{h+1}^i, a), \tilde{\theta}_{h+1} \rangle)^2 \\ &\equiv (\hat{Q} - T\theta)^2 \end{aligned}$$

earlier  $\mathcal{Q}$  = linear + terms

now  $Q = \text{linear}$

no optimism!

earlier  $EY_i \neq \text{linear}$ .

now  $EY_i$  = linear acc to Bellman Completeness.

Build in optimism using nested confidence balls

$$\text{BALL}^t := \{(\theta_1, \dots, \theta_K) : \theta_k = 0, \text{ th } R_h^{t+1}(\theta_h, \theta_{h+1}) \leq \min_{\theta} R_h^t(\theta, \theta_{h+1}) + \beta^2\}$$

$$m^{Cx} + \theta$$

Note that  $\Theta^t$  :  $R_r^{t+1}(\Theta_r^t, \Theta_{r+1}^t) = 0$

$$Q^* = T Q^{**}$$

$$\theta_t^* = r(s_{k+1}^t) + E[V_{t+1}^*(s')]$$

$$SO_h^+ \}_{h \in \mathcal{H}} \equiv \theta_1^+ - \theta_H^+$$

$$\textcircled{3} \Rightarrow (\theta_1^t, \dots, \theta_n^t) \leftarrow \arg \max_{(\theta_1, \dots, \theta_n) \in \text{BAL}^t} E_{S_t} \max_a \langle \phi(s_t, a_t), \theta_t \rangle$$

$$(\theta_1^*, \dots, \theta_n^*) \in \text{BAL}^t$$

$$F_i \max \langle \phi(s_i, a_i), \theta_i^* \rangle$$

$$\Rightarrow \text{Global optimism horizon } \rightarrow \max_a \langle \phi(s_t, a_t), \hat{\theta}_t \rangle$$

(b) greedy policy w.r.t  $\hat{\theta}^t$  to collect another episode.

Regret analysis:

$$\begin{aligned}
 \text{Regret} &\leq E\left[\sum_t \sum_h Q_h^t(s_h^t, a_h^t) - (T Q_{h+1}^t)(s_h^t, a_h^t)\right] \equiv E\left[\sum_t \sum_h \text{conf}_h^t\right] \\
 &\leq \sum_t \sum_h Q_h^t(s_h^t, a_h^t) - (T Q_{h+1}^t)(s_h^t, a_h^t) + \tilde{O}(H\sqrt{T}) \\
 &\stackrel{\text{depend on linear assumption}}{\leq} \sum_t \sum_h \underbrace{\langle \phi(s_h^t, a_h^t), \hat{\theta}_h^t - \theta_h^t \rangle}_{\text{elliptic potential lemma}} + \tilde{O}(H\sqrt{T}) \\
 &\leq \sum_t \sum_h \|\phi(s_h^t, a_h^t)\|_{\tilde{\Lambda}_{h,t-1}^{-1}} \cdot \|\hat{\theta}_h^t - \theta_h^t\|_{\tilde{\Lambda}_{h,t-1}} + \tilde{O}(H\sqrt{T}) \\
 &\quad \underbrace{\qquad\qquad\qquad}_{\text{elliptic potential lemma}} \quad \underbrace{\qquad\qquad\qquad}_{\beta = O(H\sqrt{d}) \text{ scaling fd factor using global opt.}} \\
 &= \tilde{O}(H\beta\sqrt{d}T) + \tilde{O}(H\sqrt{T}) \\
 &= \tilde{O}(H^2 d \sqrt{T})
 \end{aligned}$$

Generalization to nonlinear functions.

- only place linear assumption needed is to bound  $\|\hat{\theta}_h^t - \theta_h^t\|_d$

Notion for nonlinear complexity

Bellman rank: Given  $\mathcal{F}$ , let  $\Pi$  be induced policy class

$\Pi = \{\Pi_f : f \in \mathcal{F}\}$ . For each  $h$ ,  $\exists$  embedding function

$w_h: \Pi \rightarrow \mathbb{R}^d$  and  $v_h: \mathcal{F} \rightarrow \mathbb{R}^d$  s.t.

Bellman error  $\varepsilon_h(\Pi, \mathcal{F}) = \underbrace{\langle w_h(\Pi), v_h(f) \rangle}_{Q \sim TQ}$

where  $\varepsilon_h(\Pi, \mathcal{F}) = E[Q_h(s_h, a_h) - r_h - \max_a Q_{h+1}(s_{h+1}, a)]$

d-Bellman rank

$s_h \sim d_{\Pi}^{\Pi}, a_h = \Pi_Q(s_h)$

[Note:  $Q \neq \text{linear}$ ]

not  $\Pi$  as for linear

$$\begin{aligned}
 \text{Regret: } J(\pi^*) - J(\pi) &= \sum_{t=1}^T \langle w_t(\pi^*), v_t(f^*) \rangle \quad (\text{earlier}) \\
 &\leq \sum_{t=1}^T \|w_t(\pi^*)\| \sum_{t=1}^T \|v_t(f^*)\| \Sigma_{t=1}^T \\
 \text{assuming } \|w_t(\pi)\|_2 &\leq W, \|v_t(f)\|_2 \leq V \quad \lambda I + \Sigma_{t=1}^T V V^T = \\
 \text{can show } \|v_t(f^*)\|_{\Sigma_{t=1}^T} &\leq \sqrt{\lambda V^2 + 4\beta^2} = \|\theta - \hat{\theta}\| \\
 \|w_t(f^*)\|_{\Sigma_{t=1}^T} &\leq \sqrt{2Hd \log T} \quad ) \quad \text{elliptic potential lemma}
 \end{aligned}$$

$\Rightarrow$  Regret bound that depends on Bellman rank d.