2.1 a naive model-based approach

## Central question:

Do we require an accuracy model of the world to find a near optimal policy?

A naive model to learn P: after sampling N times, let  $\hat{P}(s'|s,a) = \frac{count(s',s,a)}{N}$  here we view  $\hat{P}$  as a matrix of size |S|/A[x|S]

Expectation: O(ISI2IAI) obeservation is enough for an accurate model.

Proposition 2.1 Assume  $e \in (0, \frac{1}{1-\gamma})$ ,  $\exists c > 0 \leq t$ .

# samples from generative model

=  $|S||A|N > \frac{4c^2}{(1-\gamma)^4} \frac{|S||og(1/8)}{5^2}$  [different from book ]

where (s,a) is sampled uniformly, and with prob. 71-8 we have

- ① (Model accuracy)  $\max_{s_1,a} ||P(\cdot|s,a) \hat{P}(\cdot|s,a)||_1 \leq (1-\gamma)^2 \epsilon$
- ② (Uniform value accuracy)  $||Q^{\pi} \hat{Q}^{\pi}||_{\infty} \leq \frac{2}{2} \quad \text{for all } \pi$
- 3 (Near optimal planning) Suppose  $\hat{\pi}$  is optimal w.r.t.  $\hat{M}$   $\|\hat{Q}^* Q^*\|_{\infty} \leq \frac{\epsilon}{2}$ ,  $\|Q^{\hat{\pi}} Q^*\|_{\infty} \leq \epsilon$

To show this, we need following lemmas.

Lemma 2.2 [Simulation lemma] For all 
$$\pi$$
: 
$$Q^{\pi} - \hat{Q}^{\pi} = \gamma (I - \gamma \hat{P}^{\pi})^{-1} (P - \hat{P}) V^{\pi}.$$

$$Pf: Q^{\pi} - \hat{Q}^{\pi} = Q^{\pi} - (I - \Upsilon \hat{p}^{\pi})^{-1} r$$

$$= (I - \Upsilon \hat{p}^{\pi})^{-1} ((I - \Upsilon \hat{p}^{\pi}) Q^{\pi} - r)$$

$$= (I - \Upsilon \hat{p}^{\pi})^{-1} ((I - \Upsilon \hat{p}^{\pi}) - (I - \Upsilon \hat{p}^{\pi})) Q^{\pi}$$

$$= \Upsilon (I - \Upsilon \hat{p}^{\pi})^{-1} (p^{\pi} - \hat{p}^{\pi}) Q^{\pi}$$

$$= \Upsilon (I - \Upsilon \hat{p}^{\pi})^{-1} (p - \hat{p}) V^{\pi}$$

Lemma 2.3 For any policy  $\pi$ , MDP M and  $V \in \mathbb{R}^{|S||A|}$   $||(I - \Upsilon p^{\pi})^{-1} V||_{\infty} \leq \frac{1}{|-\Upsilon|} ||V||_{\infty}$ 

Pf: 
$$V = (I - \Upsilon P^{\pi})(I - \Upsilon P^{\pi})^{-1}V = :(I - \Upsilon P^{\pi})W$$

$$\Rightarrow \|V\|_{\infty} = \|(I - \Upsilon P^{\pi})W\|_{\infty}$$

$$\Rightarrow \|W\|_{\infty} - \Upsilon \|P^{\pi}W\|_{\infty}$$

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$$= (I - \Upsilon)\|W\|_{\infty}$$

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$$= (I - \Upsilon P^{\pi})^{-1}V\| \leq I - \Upsilon \|V\|_{\infty}$$

Lemma A.8 [concentration for discrete distributions] Let z be r.v. of  $\{1, \dots, d\}$ , distributed according to q, where  $\overline{q} = [P_r(z=j)]_{j=1}^d$ . Assume we have N i.i.d. samples and that our empirical estimate is  $[\widehat{q}]_j = \sum_{i=1}^N \mathbb{1}_{i} \mathbb{1}$ 

which implies:

## Pr(119-9111)> Ta( +2)) ≤ e-Ne2

this proof is ignored

Pf of Proposition 2.1:

with  $l_1$  norm in lemma A.8, for fixed s, a, with prob.  $\geq 1-8$ , we have

$$\|p(\cdot|s,a) - \hat{p}(\cdot|s,a)\|_1 \le c\sqrt{\frac{|s|\log(1/8)}{m}}$$
 (\*)

where m is the number of samples used to estimate  $\hat{p}(\cdot|s,a)$ . just let  $s=e^{-m\epsilon^2} \Rightarrow \epsilon = \sqrt{\frac{\log(1/\epsilon)}{m}}$ , d=|s| and let c satisfy  $c\sqrt{\frac{|s|\log(1/\epsilon)}{m}} \geqslant \sqrt{|s|}(\sqrt{\frac{1}{m}} + \epsilon)$ 

- ①  $||p(\cdot|s,a) \hat{p}(\cdot|s,a)||_{1} \leq (1-\Upsilon)^{2} \epsilon$ Since  $m \geq \frac{4C^{2}}{(1-\Upsilon)^{4}} \frac{|s|\log(1/8)}{\epsilon^{2}}$ , by (\*) we have  $||p(\cdot|s,a) - \hat{p}(\cdot|s,a)||_{1} \leq (1-\Upsilon)^{2} \epsilon/2$  with prob.  $\geq 1-8$

3 
$$\|\hat{Q}^* - Q^*\|_{\infty} \le \frac{2}{5}$$
,  $\|Q^{\pi} - Q^{\pi^*}\|_{\infty} \le 2$   
observe that  $\|\sup f(x) - \sup g(x)\| \le \sup \|f(x) - g(x)\|$   
 $= \|\hat{Q}^*(s,a) - Q^*(s,a)\| = \|\sup \hat{Q}^{\pi}(s,a) - \sup Q^{\pi}(s,a)\|$   
 $\le \sup \|\hat{Q}^{\pi}(s,a) - Q^{\pi}(s,a)\|$ 

$$\begin{split} \|Q^{\hat{\pi}} - Q^{\pi^*}\|_{\infty} &\leq \|Q^{\hat{\pi}} - \hat{Q}^*\|_{\infty} + \|\hat{Q}^* - Q^{\pi^*}\|_{\infty} \\ &= \|Q^{\hat{\pi}} - \hat{Q}^{\hat{\pi}}\|_{\infty} + \|\hat{Q}^* - Q^*\|_{\infty} \\ &\leq \frac{2}{2} + \frac{2}{2} = 2 \end{split}$$