

Marginalized Importance Sampling (MIS)

$$\rho_{1:H} \sim (\pi/\pi_b)^H$$

- IS: exponential variance unless $\pi \approx \pi_b$.
- FQE. (policy-eval ver. of FQ2).

$$f_{k+1} \leftarrow \underset{f \in \mathcal{F}}{\operatorname{argmin}} \frac{1}{|D|} \sum_{(s,a,r,s')} (f(s,a) - r - \gamma f(s',\pi))^2$$

$$\forall f \in \mathcal{F}, \mathcal{T}^\pi f \in \mathcal{F}$$

\Rightarrow w/ \mathcal{F} bounded complexity. poly sample size.

$$\| f_{k+1} - \mathcal{T}^\pi f_k \|_{2,\mu} = \varepsilon$$

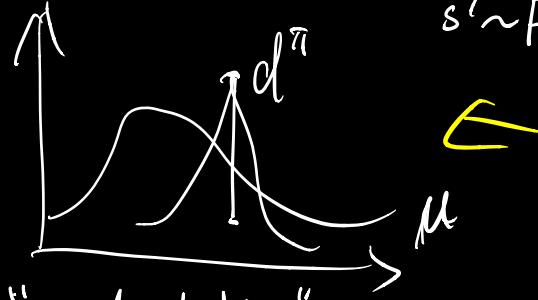
$$\Rightarrow \left\| \frac{d^\pi}{\mu} \right\|_\infty \leq C.$$

$(s,a) \sim \mu, r \sim R(s,a)$

$s' \sim P(\cdot | s,a)$.

$$\Rightarrow \left| J(\pi) - \mathbb{E}_{\substack{s \sim d_\mu \\ a \sim \pi(a|s)}} [f_k(s, \pi)] \right|$$

$$\leq \text{poly}(C) \cdot \varepsilon. \quad \text{"realizability."}$$



- Problem w/ FQE: $Q^\pi \in \mathcal{F}$ is insufficient

- Is there method w/ func-approx error? monotone.

- Is there anything we can do if we only have $\underline{Q^\pi \in \mathcal{F}}$.

\Rightarrow MIS address both questions.

Dai, Nachum... "DICE", "M-L".

"density estimation" ...

$$MDP = (S, A, P, R, \gamma, s_0) \text{ d.}$$

$$\text{W.t. learn } J(\pi) = Q^\pi(s_0, \pi) = \frac{1}{1-\gamma} \mathbb{E}_{(s,a) \sim d^\pi} [r].$$

have data: $(s, a) \sim \mu, r \sim R(s, a), s' \sim p(\cdot | s, a)$ \$r \sim R(s, a)\$

"Eval error Lemma for \$\mathcal{Q}\$":

TD/Bellman err.

$$\text{Af. } \underline{J(\pi)} - \mathcal{Q}(s_0, \pi) = \frac{1}{1-\gamma} \mathbb{E}_{(s,a) \sim d^\pi} [r + \gamma \mathcal{Q}(s', \pi) - \mathcal{Q}(s, a)].$$

$$\text{Prof: } d^\pi = (1-\gamma) \sum_{t=1}^{\infty} \gamma^{t-1} d_t^\pi \xrightarrow{\text{dist. of } (s_t, a_t) \text{ under policy } \pi.}$$

$$\text{RHS} = \mathbb{E}_{(s,a) \sim d_1^\pi} [r + \gamma \mathcal{Q}(s', \pi) - \mathcal{Q}(s, a)] \quad (s, a) \sim d_1^\pi, s' \sim p(\cdot | s, a), a' \sim \pi(\cdot | s).$$

$$+ \frac{\gamma}{\gamma} \mathbb{E}_{(s,a) \sim d_2^\pi} [r + \gamma \mathcal{Q}(s', \pi) - \mathcal{Q}(s, a)].$$

\vdots

$$\mathbb{E} \left[\sum_{t=1}^{\infty} \gamma^{t-1} r_t \mid \pi \right].$$

$$= \sum_{t=1}^{\infty} \gamma^{t-1} \mathbb{E}_{(s,a) \sim d_t^\pi} [r] - \mathbb{E}_{(s,a) \sim d_1^\pi} [\mathcal{Q}(s, a)].$$

$$= J(\pi) - \mathcal{Q}(s_0, \pi) = \text{LHS.} \quad \blacksquare$$

$$\text{Alt. Proof: } J(\pi) = \frac{1}{1-\gamma} \mathbb{E}_{(s,a) \sim d^\pi} [r].$$

$$\text{the remaining: } 0 = \mathcal{Q}(s_0, \pi) + \frac{1}{1-\gamma} \mathbb{E}_{(s,a) \sim d^\pi} [\mathcal{Q}(s', \pi) - \mathcal{Q}(s, a)]$$

"Bellman off for occupancy"

$$d^\pi = \begin{bmatrix} d_1^\pi \\ \gamma d_2^\pi \\ \gamma^2 d_3^\pi \\ \gamma^3 d_4^\pi \end{bmatrix}$$

$$\xrightarrow{\text{distr. of } (s_t, a_t) \text{ under policy } \pi} \begin{bmatrix} d_1^\pi \\ \gamma d_2^\pi \\ \gamma^2 d_3^\pi \\ \gamma^3 d_4^\pi \end{bmatrix}$$

Goal: find \hat{g} . s.t. minimize.

$$\min_{\hat{g}} \left| J(\pi) - \hat{g}(s_0, \pi) \right| = \left| \frac{1}{1-\gamma} \mathbb{E}_{d^\pi} [r + \gamma \hat{g}(s', \pi) - \hat{g}(s, a)] \right| \leq$$

$$= \left| \frac{1}{1-\gamma} \mathbb{E}_{(s,a) \sim \mu} \left[\frac{d^\pi(s,a)}{\mu(s,a)} (r + \gamma \hat{g}(s', \pi) - \hat{g}(s,a)) \right] \right|$$

Assume: $w^\pi/\mu \in W$

$$\leq \sup_{w \in W} \frac{1}{1-\gamma} \left| \mathbb{E}_\mu [w(s,a)(r + \gamma \hat{g} - \hat{g})] \right|$$

$w^\pi/\mu(s,a)$
 "marginalized imp."
 "density ratio".
 "weight"

side. comment.

$$\mathbb{E}_g \left[\frac{P(x)}{g(x)} f(x) \right]. \quad \text{suppose.}$$

$$y = g(x)$$

$$f(x) = f'(y).$$

$$\mathbb{E}_g \left[\frac{P_Y(y)}{g_f(y)} f'(y) \right]$$

in general:

$$\text{Var} \left[\frac{P_Y(y)}{g_f(y)} \right] \subseteq \text{Var} \left[\frac{f(x)}{g(x)} \right]$$

$P_{1:H} = \prod \frac{\pi(a_t | s_t)}{\pi(a_t | s_t)} = \frac{P^\pi(s_1, a_1, s_2, a_2, \dots, s_H, a_H)}
 $\downarrow w^\pi/\mu = \frac{P^\pi(s_t, a_t)}{P^{\pi_b}(s_t, a_t)}$
 ← or arbitrary μ .
 in our ctx.
 $x = s_1, a_1, s_2, a_2, \dots, s_H, a_H$.
 $g(x) = s_t, a_t$.$

$$|J(\pi) - \hat{g}(s_0, \pi)| \leq \sup_{w \in W} \frac{1}{1-\gamma} \left| \mathbb{E}_\mu [w(s,a)(r + \gamma \hat{g}(s', \pi) - \hat{g}(s,a))] \right|$$

Alg: over \mathcal{Q} class assuming $w^\pi/\mu \in W$ (convex to

$$\arg \min_{\hat{g} \in \mathcal{Q}} \sup_{w \in W} \left| \mathbb{E}_\mu [w \cdot (r + \gamma \hat{g} - \hat{g})] \right| \quad w^\pi/\mu \in \text{conv}(W)$$

"MQL [Veham et al '20]."

Why relaxation from W^π/μ to $\sup_{w \in W}$ makes sense
 \rightarrow Ideally $g = Q^\pi$ \rightarrow "tight relaxation"
 for this func. loss: $\sup_{w \in W} \mathbb{E}_\mu [w \cdot (r + \gamma g(s', \pi)) - g(s, a)] = 0.$

\rightarrow MQL: $\begin{cases} \text{when } W^\pi/\mu \in W \\ \text{when } Q^\pi \in Q: \text{upper bound can be minimized to 0} \end{cases}$ Valid upper bound of $|\mathcal{J}(\pi) - \mathcal{E}(s, \pi)|$.

\rightarrow "g generator" \rightarrow "w discriminator".

$"MWL"$ \rightarrow find g : s.t. $\rightarrow \mathbb{E}_\mu [w(s, a) - (g(s, a) - r - \gamma g(s', \pi))] = 0.$ different: $\ g - \mathcal{T}^\pi g\ _{2, \mu}^2$ $= \mathbb{E}_\mu [(g(s, a) - \mathbb{E}_{V, S' S, a} [r + \gamma g(s', \pi)])^2]$	$"w \text{ generator}"$ Bellman error. \downarrow \downarrow \downarrow	$"g \text{ discriminator}"$ LSTD. avg Bellman eq. compare \Rightarrow sq. ptwise. ult. view of MQL.
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Want to learn w . s.t.

$$\overline{J}(\pi) = \frac{1}{1-\gamma} \mathbb{E}_\mu [w^\top \cdot r]$$

$$= Q^\pi(s_0, \pi) + \frac{1}{1-\gamma} \mathbb{E}_\mu [w(s, a) \cdot (\gamma Q^\pi(s', \pi) - Q^\pi(s, a))]. \quad \triangle$$

Proof: $\frac{1}{1-\gamma} \mathbb{E}_\mu [w(s, a) \cdot (\underbrace{r + \gamma Q^\pi(s', \pi) - Q^\pi(s, a)}_{\mathbb{E}[\cdot | s, a]})] = 0.$

find w . s.t. $| \overline{J}(\pi) - \frac{1}{1-\gamma} \mathbb{E}_\mu [w(s, a) \cdot r] | < 0.$

Assume $Q^\pi \in \mathcal{Q}$. $\leq \sup_{g \in \mathcal{Q}} | (Q(s_0, \pi) + \frac{1}{1-\gamma} \mathbb{E}_\mu [w \cdot (\gamma g - g)]) |$

"MWL": $\arg \min_{w \in \mathcal{W}} \sup_{g \in \mathcal{Q}} \overline{J}(\pi) \in \frac{1}{1-\gamma} \mathbb{E}_\mu [\hat{w} \cdot r] + \sup_g L_W(\hat{w}, g)$

Relaxation is "tight": $w = w^\top \mu$

$\forall g: \underline{Q}(s_0, \pi) + \frac{1}{1-\gamma} \mathbb{E}_d [\gamma \underline{Q}(s', \pi) - \underline{Q}(s, a)]$

 $= \langle \underline{Q}, \cancel{\text{do } x \pi} \cdot \frac{1}{1-\gamma} d^\pi + \frac{\gamma}{1-\gamma} ((P^\top d^\pi) \times \pi) \rangle$
 $= 0.$

so, if $Q^\pi \in \mathcal{Q} \Rightarrow$ valid upper bound.

$w^\top \mu \in \mathcal{W} \Rightarrow$ minimize upper bound. ↗
(to 0).

$$\boxed{J(\pi) = \frac{1}{1-\gamma} E_{\mu}[\omega \cdot r] + Q^{\pi}(s_0, \pi) + \frac{1}{1-\gamma} E_{\mu}[w(\gamma Q^{\pi}(s', \pi) - Q^{\pi}(s, a))].}$$

$$\boxed{J(\pi) = g(s_0, \pi) + \frac{1}{1-\gamma} E_{d^{\pi}}[r + \gamma g(s', \pi) - g(s, a)].}$$

Define $L(w, g) = \frac{1}{1-\gamma} E_{\mu}[\omega \cdot r] + g(s_0, \pi) + \frac{1}{1-\gamma} E_{\mu}[w(\gamma g(s', \pi) - g(s, a))]$.

$$J(\pi) = L(w, Q^{\pi}) = L(w^{\pi/\mu}, g) \quad \forall w, g.$$

$\boxed{Q^{\pi} \in \mathcal{Q}}$ then:

$$\text{Hw. } J(\pi) = L(w, Q^{\pi}) \leq \sup_{g \in \mathcal{Q}} L(w, g) \quad \xrightarrow{J(\pi) \in \inf_g L(w, g)} \text{Hw.}$$

$$\geq \inf_{g \in \mathcal{Q}} L(w, g)$$

$$\Rightarrow \sup_{w \in W} \inf_{g \in \mathcal{Q}} L(w, g) \leq J(\pi) \leq \inf_{w \in W} \sup_{g \in \mathcal{Q}} L(w, g) \quad \checkmark.$$

$$\boxed{w^{\pi/\mu} \in W} \quad \text{Hg. } \inf_{w \in W} L(w, g) = J(\pi) = L(w^{\pi/\mu}, g) \leq \sup_{w \in W} L(w, g)$$

$$\Rightarrow \sup_{g \in \mathcal{Q}} \inf_{w \in W} L(w, g) \leq J(\pi) \leq \inf_{g \in \mathcal{Q}} \sup_{w \in W} L(w, g). \quad \checkmark$$

Sion's minimax thm: b/c $L(w, g)$ is convex-concave, n.
and W & \mathcal{Q} are convex.

$$\Rightarrow \sup_{g \in \mathcal{Q}} \inf_w L(w, g) = \inf_w \sup_{g \in \mathcal{Q}} L(w, g).$$

Why misspecification?

$$\underline{W}^{\pi/\mu} \neq \underline{W}$$

$\boxed{d''}$
 $\boxed{\mu}$

$$\underline{Q}^{\pi} \notin \boxed{\underline{Q}}$$

How about learning? For DPE, we learn \underline{Q}^{π}

For learning, we try to learn \underline{Q}^* .

$$\max_{\pi \in \mathcal{Q}} Q^*(s, a)$$

$$\Rightarrow \forall w. \quad \mathbb{E}_{\mu} \left[w(s, a) \cdot (\underline{Q}^*(s, a) - r - \gamma V_{\underline{Q}^*}(s')) \right] = 0.$$

MABO

$$\arg \min_{g \in \mathcal{Q}} \max_{w \in W}$$

$$\nearrow g \in \mathcal{Q}$$

$$\mathbb{E}_{\mu} \left[w \cdot (\underline{g}(s, a) - r - \gamma V_g(s')) \right]$$

output π_g . ← When near-optimal?

Func-approx: ① $\underline{Q}^* \in \mathcal{Q}$.

② $\forall \pi_g$ s.t. $g \in \mathcal{Q}$, $\frac{d^{\pi_g}}{\mu} \in W$.

Lemma:

$$\forall g. \quad \mathbb{E}_{d^{\pi_g}} [r + \gamma \underline{g}(s', \pi_g) - g(s, a)]$$

$$\bar{J}(\pi) - \bar{J}(\pi_g) \leq \frac{1}{1-\gamma} \left(\mathbb{E}_{d^{\pi^*}} [\underline{T}_g - g] + \mathbb{E}_{d^{\pi_g}} [g - \underline{T}_g] \right).$$

Proof: Recall eval error lemma:

$$\forall \pi, \quad \bar{J}(\pi) - \underline{g}(s_0, \pi) = \frac{1}{1-\gamma} \mathbb{E}_{d^{\pi}} [r + \gamma \underline{g}(s', \pi) - g(s, a)],$$

$$\bar{J}(\pi^*) - \bar{J}(\pi_g) = \bar{J}(\pi^*) - \underline{g}(s_0, \pi_g) + \underline{g}(s_0, \pi_g) - \bar{J}(\pi_g),$$

$$\leq \bar{J}(\pi^*) - \underline{g}(s_0, \pi^*). + \underline{g}(s_0, \pi_g) - \bar{J}(\pi_g).$$

↓ eval π^* w.e.g.

$$= \frac{1}{1-\gamma} \mathbb{E}_{d^{\pi^*}} [r + \gamma \underline{g}(s', \pi^*) - g(s, a)] - \frac{1}{1-\gamma} \mathbb{E}_{d^{\pi_g}} [r + \gamma \underline{g}(s', \pi_g) - g(s, a)]$$

$$\leq \frac{1}{1-\gamma} \mathbb{E}_{d^{\pi^*}} [r_t + \gamma Q(s', \pi_\theta) - q(s, a)] - \frac{1}{1-\gamma} \mathbb{E}_{d^{\pi_\theta}} [\mathbb{V}_\theta].$$

$$= \frac{1}{1-\gamma} \mathbb{E}_{d^{\pi^*}} [\mathbb{V}_\theta] - \frac{1}{1-\gamma} \mathbb{E}_{d^{\pi_\theta}} [\mathbb{V}_\theta]. \quad \square$$

$$\arg \min_w \max_{\pi_\theta} \left\{ \dots \right\}$$
