A Theoretical Justification for Asymmetric Actor-Critic Algorithms

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Asymmetric Observability

Partial observability

A **POMDP** is described by a model $\mathcal{P} = (\mathcal{S}, \mathcal{A}, \mathcal{O}, P, O, T, R, \gamma)$.

- States $s_t \in \mathcal{S}$,
- Actions $a_t \in \mathcal{A}$,
- Observations $o_t \in \mathcal{O}$,
- Initialization $s_0 \sim P(\cdot)$,
- Perception $o_t \sim O(\cdot\,|s_t)$,
- Transition $s_{t+1} \sim T(\cdot\,|s_t, a_t)$,
- Reward $r_t \sim R(\cdot\,|s_t, a_t)$,
- Discount $\gamma \in [0, 1)$.

The **history** at time t is $h_t = (o_0, a_0, ..., o_t) \in \mathcal{H}$.

Definition 1: History-dependent stochastic policy.

A history-dependent stochastic policy $\pi \in \Pi = \mathcal{H} \to \Delta(\mathcal{A})$ is a mapping from histories to distributions over the actions, with density $\pi(a|h)$.

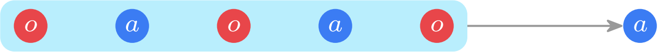


Fig. 1: History-dependent policy.

Learning under partial observability

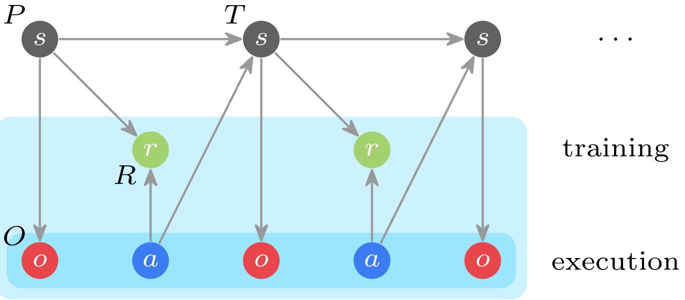


Fig. 2: Bayesian graph of a POMDP.

The problem of **RL in POMDP** is to find an optimal history-dependent policy

$$\pi^* \in \operatorname*{argmax}_{\pi \in \Pi} \mathbb{E}^{\pi} \left[\sum_{t=0}^{\infty} \gamma^t R_t \right]$$

from samples $(o_0, a_0, r_0, \ldots, o_t)$.

Asymmetric observability

Decision process	Execution	Training	Generality
MDP	s	s	**Too optimistic.**
POMDP	o	o	**Too pessimistic.**
Privileged POMDP	o	s	**Too optimistic.**
Informed POMDP	o	i	**Just right?**

Examples: simulator state, trajectory in hindsight, additional sensors, additional viewpoints, observations of other agents, etc.

Learning under asymmetric observability

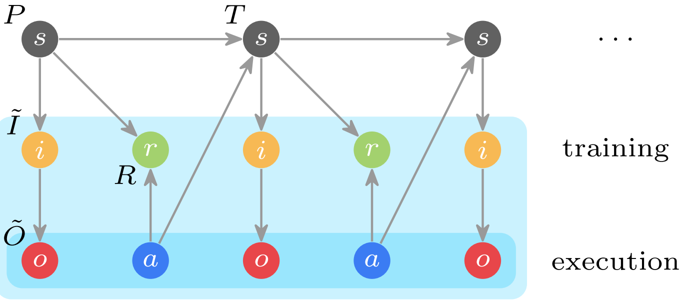


Fig. 3: Bayesian graph of an informed POMDP.

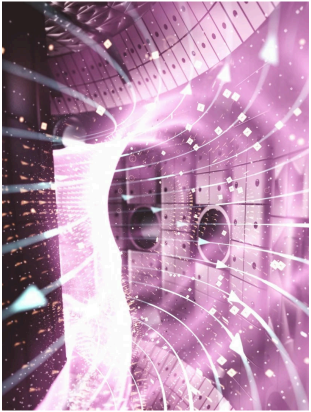
The problem of **RL in POMDP** is to find an optimal history-dependent policy

$$\pi^* \in \operatorname*{argmax}_{\pi \in \Pi} \mathbb{E}^{\pi} \left[\sum_{t=0}^{\infty} \gamma^t R_t \right]$$

from samples $(i_0, o_0, a_0, r_0, \dots, i_t, o_t)$.

Asymmetric learning is successful

- Magnetic Control of Tokamak Plasma through Deep RL (Degrave et al., 2022).
- Champion-Level Drone Racing using Deep RL (Kaufmann et al., 2023).
- A Super-Human Vision-Based RL Agent in Gran Turismo (Vasco et al., 2024).



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Asymmetric Learning

1. Imitation learning approaches

The idea consists of imitating an expert policy (Choudhury et al., 2018):

1. Learn a policy for the MDP: $\mu(a|s)$,
2. Imitate the policy: $\pi(a|h) \approx \mu(a|s)$.

It is known to be suboptimal: the policy corresponds to the greedy policy with respect to the Q-MDP approximation (Littman et al., 1995):

$$\hat{V}_{\text{POMDP}}(h) = \mathbb{E}[V_{\text{MDP}}(S)|H = h].$$

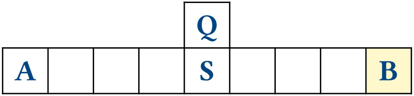

Fig. 4: Environment with random unobserved goal where imitation is optimal.

Recent works have constrained the expert policy such that its imitation results in an optimal history-dependent policy (Warrington et al., 2021).

2. Asymmetric critic approaches

The idea comes from the lack of need of the critic at execution (Pinto et al., 2018):

1. The policy is conditioned on the history: $\pi(a|h)$.
2. The critic is conditioned on the state: $Q(s, a)$.
3. The policy gradient is approximated using: $\log \pi(a|h) Q(s, a)$.

It is known to be biased or even ill-defined: the environment state s is not a Markovian state of the future execution of the environment and policy $\pi(a|h)$.

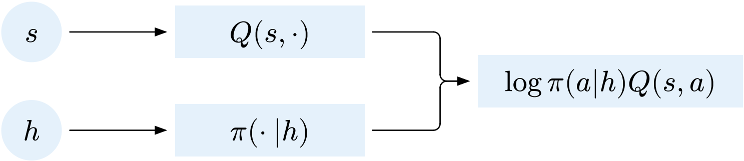

Fig. 5: Illustration of the asymmetric actor-critic.

Recent works have proposed a well-defined and unbiased asymmetric actor-critic by introducing the history-state critic $Q(h, s, a)$ (Baisero & Amato, 2022).

3. Representation learning approaches

The idea comes from the sufficiency of the belief (Nguyen et al., 2021).

1. The history is compressed into a statistic: $z = f(h)$.
2. The statistic is trained to be predictive of the belief: $\hat{b}(s|z) \approx p(s|h)$.
3. The policy is conditioned on that statistic: $\pi(a|h) = g(a|z)$.

It is known to be unrealistic: computing the belief $p(s|h)$ requires the dynamics to be known and is in general intractable.

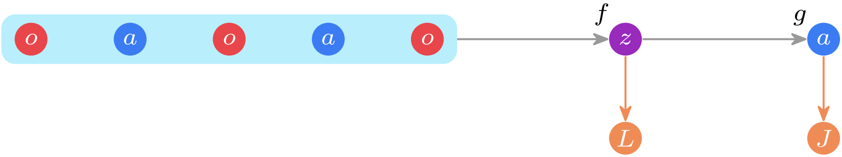

Fig. 6: Representation learning in POMDP.

Recent works have proposed to learn belief representations from the sample states that are observed at training time (Wang et al., 2023).

4. Model-based learning approaches

Several concurrent approaches to replace the word model $q(r, o'|h, a)$:

- **Bisimulation** of belief world model (Avalos et al., 2024):
  1. Predict the belief: $b = f(h)$.
  2. Learn a belief world model: $b' = g(b, a, o')$.
- **Representation learning** with asymmetric model (Lambrechts et al., 2024):
  1. Predict the next information: $q(r, i'|h, a)$.
  2. Use latent policy to learn from the informed world model.
- **Distillation** of a privileged world-model (Hu et al., 2024):
  1. Learn a privileged world model: $q(r, o'|h^+, a)$.
  2. Distillate the world model: $q(r, o'|h, a)$.

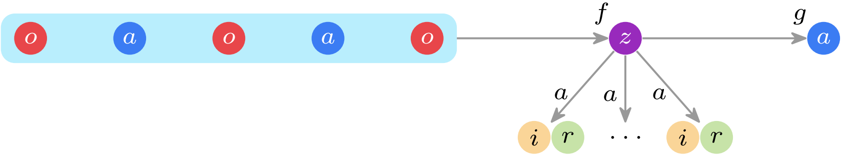

Fig. 7: Informed world model.

A Theoretical Justification for Asymmetric Actor-Critic Algorithms

Lack of justification

To sum up, while early approaches were **heuristic**, a recent line of work has focused on proposing **theoretically grounded** objectives:

- They provide optimal history-dependent policies when satisfied,
- They make use of the additional state information.

But there are still **no theoretical justification for the benefits**. While at optimality policies are equivalent, asymmetric learning should converge faster.

Goal of this work: justification for the asymmetric actor-critic algorithm.

NB: Some explanations exist in the literature (Baisero & Amato, 2022; Sinha & Mahajan, 2023). Recently, an asymmetric actor-critic relying on learning beliefs was shown more efficient than symmetric learning (Cai et al., 2024).

Asymmetric actor-critic algorithm

We make the following assumptions:

- **Discrete space:**
  - State space $\mathcal{S}$, observation space $\mathcal{O}$, action space $\mathcal{A}$.
  - Agent state space $\mathcal{Z}$.
- **Finite state policy:**
  - Agent state process $z_{t+1} \sim U(\cdot\,|z_t, a_t, o_{t+1})$.
  - Policy $a_t \sim \pi(\cdot\,|z_t)$.
- **Finite state Q-functions:**
  - Asymmetric $\mathcal{Q}^\pi(s, z, a) = \mathbb{E}^\pi\left[\sum_{t=0} \gamma^t R_t | S_0 = s, Z_0 = z, A_0 = a\right]$.
  - Symmetric $Q^\pi(z, a) = \mathbb{E}^\pi\left[\sum_{t=0} \gamma^t R_t | Z_0 = z, A_0 = a\right]$.
- **Linear Q-functions approximations:**
  - Asymmetric $\hat{\mathcal{Q}}^\pi_\beta(\cdot) = \langle \beta, \varphi(\cdot) \rangle$ with $\varphi : \mathcal{S} \times \mathcal{Z} \times \mathcal{A} \to \mathbb{R}^d$.
  - Symmetric $\hat{Q}^\pi_\beta(\cdot) = \langle \beta, \chi(\cdot) \rangle$ with $\chi : \mathcal{Z} \times \mathcal{A} \to \mathbb{R}^d$.
- **Log-linear policy:**
  - $\pi_\theta(a|z) \propto \exp(\langle \theta, \psi(z, a) \rangle)$.

Asymmetric actor-critic algorithm (ii)

We use the abbreviations $\hat{\mathcal{Q}}^{\pi}_{k,i} = \hat{\mathcal{Q}}^{\pi}(s_{k,i}, z_{k,i}, a_{k,i})$ and $\hat{Q}^{\pi}_{k,i} = \hat{Q}^{\pi}(z_{k,i}, a_{k,i})$.

The **asymmetric semi-gradient** is,

$$g_k = \left(\sum_{i=0}^{m-1} \gamma^i r_{k,i} + \gamma^m \hat{\mathcal{Q}}^{\pi}_{k,m} - \hat{\mathcal{Q}}^{\pi}_{k,0} \right) \nabla_{\beta} \hat{\mathcal{Q}}^{\pi}_{k,0}. \tag{1}$$

and the **symmetric semi-gradient** is,

$$g_k = \left(\sum_{i=0}^{m-1} \gamma^i r_{k,i} + \gamma^m \hat{Q}^{\pi}_{k,m} - \hat{Q}^{\pi}_{k,0} \right) \nabla_{\beta} \hat{Q}^{\pi}_{k,0}. \tag{2}$$

Interestingly, the asymmetric Q-function $\mathcal{Q}(s, z, a)$ is the solution of its Bellman equation, while the symmetric Q-function $Q(z, a)$ is not!

Asymmetric actor-critic algorithm (iii)

Algorithm 1: m-step TD learning.

```
1. For $k = 0, \ldots, K - 1$:
   1. Sample $s_{k,0}, z_{k,0}$ from the discounted visitation measure $d^{\pi}(\cdot)$.
   2. For $i = 0, \ldots, m - 1$:
      1. Take action $a_{k,i} \sim \pi\left(\cdot \mid z_{k,i}\right)$.
      2. Observe $r_{k,i+1}, s_{k,i+1}, o_{k,i+1}, z_{k,i+1}$ according to $R, T, O, U$.
   3. Sample last action $a_{k,m} \sim \pi\left(z_{k,m}\right)$.
   4. Compute semi-gradient $g_k$ using (1) or (2).
   5. Update parameters: $\beta_{k+1} = \Gamma_{\mathcal{B}(0,B)}(\beta_k + \alpha g_k)$.
2. Return average estimate $\overline{Q}^{\pi}(\cdot) = \langle \overline{\beta}, \varphi(\cdot) \rangle$ or $\overline{Q}^{\pi}(\cdot) = \langle \overline{\beta}, \chi(\cdot) \rangle$ with average parameter $\overline{\beta} = \frac{1}{K} \sum_{k=0}^{K-1} \beta_k$.
```

Asymmetric actor-critic algorithm (iv)

Let us define the asymmetric and symmetric advantage functions:

$$\hat{\mathcal{A}}^{\pi}(s, z, a) = \hat{\mathcal{Q}}^{\pi}(s, z, a) - \sum_{a \in \mathcal{A}} \hat{\mathcal{Q}}^{\pi}(s, z, a)$$

$$\hat{A}^{\pi}(z, a) = \hat{Q}^{\pi}(z, a) - \sum_{a \in \mathcal{A}} \hat{Q}^{\pi}(z, a).$$

We use the abbreviations $\hat{\mathcal{A}}^{\pi} = \hat{\mathcal{A}}^{\pi}(s, z, a)$ and $\hat{A}^{\pi} = \hat{A}^{\pi}(z, a)$.

Finally, the **asymmetric natural gradient loss** is,

$$v_{t,n} = \nabla_w \Big(\langle \nabla_\theta \log \pi_\theta(a_{t,n} | z_{t,n}), w_{t,n} \rangle - \overline{\mathcal{A}}_{t,n} \Big)^2. \tag{3}$$

and the **symmetric natural gradient loss** is,

$$v_{t,n} = \nabla_w \Big(\langle \nabla_\theta \log \pi_\theta(a_{t,n} | z_{t,n}), w_{t,n} \rangle - \overline{A}_{t,n} \Big)^2. \tag{4}$$

Asymmetric actor-critic algorithm (v)

Algorithm 2: Natural actor critic.

```
1. For $t = 0, ..., T - 1$:
    1. Obtain $\overline{\mathcal{Q}}^{\pi_t}$ or $\overline{Q}^{\pi_t}$ using Algorithm 1.
    2. For $n = 0, ..., N - 1$:
        1. Sample $s_{k,n}, z_{k,n}$ from the discounted visitation measure $d^{\pi}(\cdot)$.
        2. Take action $a_{k,n} \sim \pi(\cdot \mid z_{k,n})$.
        3. Compute gradient $v_{t,n}$ of the natural policy gradient using (3) or (4).
        4. Update natural policy gradient: $w_{t,n+1} = \Gamma_{\mathcal{B}(0,B)}(w_{t,n} + \zeta v_{t,n})$.
    3. Estimate natural policy gradient: $\bar{w}_t = \frac{1}{N} \sum_{n=0}^{N-1} w_{t,n}$.
    4. Update parameters $\theta_{t+1} = \theta_t + \eta \bar{w}_t$.
2. Return final policy $\pi_T = \pi_{\theta_T}$.
```

Previous finite-time bounds

Based on **previous bounds** for TD learning and NAC algorithms:

- Convergence of linear TD learning in MDP (Tsitsiklis & Van Roy, 1996).
- Finite-time analysis of linear TD learning in MDP (Bhandari et al., 2021).
- Finite-time analysis of log-linear NAC in MDP (Agarwal et al., 2021).

We **adapt existing bounds** for TD and NAC in POMDP (Cayci et al., 2024):

- It **does not assume** a stationary distribution nor full rank feature matrices.
- It **does assume** to sample i.i.d. from the discounted visitation measure.

These adaptations resulted in the following **contributions**:

- Fixing a few typos and errors in the original proofs.
- Adapting it to $z_t \sim f(\cdot\,|h_t)$ instead of $z_t \sim f(\cdot\,|h_{t-1}, a_{t-1})$.
- Generalizing these bounds to the asymmetric learning setting.

We define the belief $b(s|h) = \Pr(s|h)$ and approximate belief $\hat{b}(s|z) = \Pr(s|z)$.

Finite-time bound for the critics

Theorem 1: Finite-time bound for symmetric and asymmetric Q-functions.

For any $\pi \in \Pi_{\mathcal{M}}$, and any $m \in \mathbb{N}$, we have for Algorithm 1 with $\alpha = \frac{1}{K}$,

$$\sqrt{\mathbb{E}\left[\left\|\mathcal{Q}^\pi - \overline{\mathcal{Q}}^\pi\right\|_{d^\pi}^2\right]} \leq \varepsilon_{\text{td}} + \varepsilon_{\text{app}} + \varepsilon_{\text{shift}}$$

$$\sqrt{\mathbb{E}\left[\left\|Q^\pi - \overline{Q}^\pi\right\|_{d^\pi}^2\right]} \leq \varepsilon_{\text{td}} + \varepsilon_{\text{app}} + \varepsilon_{\text{shift}} + \varepsilon_{\text{alias}}.$$

$$\varepsilon_{\text{td}} = \sqrt{\frac{4B^2 + \left(\frac{1}{1-\gamma} + 2B\right)^2}{2\sqrt{K}(1-\gamma^m)}}$$

$$\varepsilon_{\text{app}} = \frac{1+\gamma^m}{1-\gamma^m} \min_{f \in \mathcal{F}_\varphi^B} \left\|f - Q^\pi\right\|_{d^\pi}$$

$$\varepsilon_{\text{shift}} = \left(B + \frac{1}{1-\gamma}\right)\sqrt{\frac{2\gamma^m}{1-\gamma^m}\sqrt{\left\|d_m^\pi \otimes \pi - d^\pi \otimes \pi\right\|_{\text{TV}}}}$$

$$\varepsilon_{\text{alias}} = \frac{2}{1-\gamma}\left\|\mathbb{E}^\pi\left[\sum_{k=0}^{\infty} \gamma^{km}\left\|\hat{b}_{k,m} - b_{k,m}\right\|_{\text{TV}} \,\middle|\, Z_0 = \cdot, A_0 = \cdot\right]\right\|_{d^\pi}.$$

Sketch of the critic proof

We can easily show that for any $l \in \mathbb{R}$,

$$\sqrt{\mathbb{E}\left[\left\|Q-\overline{Q}\right\|_d^2\right]} \leq \left\|Q-\tilde{Q}\right\|_d^2 + \underbrace{\sqrt{\frac{1}{K}\sum_{k=0}^{K-1}\left(\underbrace{\mathbb{E}\left[\sqrt{\left\|\tilde{Q}-\hat{Q}_k\right\|_d^2}\right]}_{\Delta_k} - l\right)^2}}_{(*)} + l.$$

We bound $(*)$ for $l = \frac{1+\gamma^m}{1-\gamma^m}\left(\left\|\hat{Q}_* - Q\right\|_d + \left\|Q-\tilde{Q}\right\|_d\right)$ by bounding the drift,

$$\mathbb{E}\left[\left\|\beta_* - \beta_{k+1}\right\|_d^2 - \left\|\beta_* - \beta_k\right\|_d^2\right] \leq -(\ldots)(\Delta_k - l)^2 + (\ldots)l^2 + (\ldots).$$

By summing all Lyapounov drifts and rearranging,

$$\frac{1}{K}\sum_{k=0}^{K-1}(\Delta_k - l)^2 \leq -\frac{1}{K(\ldots)}\mathbb{E}\left[\left\|\beta_* - \beta_K\right\|_d^2 - \left\|\beta_* - \beta_0\right\|_d^2\right] + (\ldots)l^2 + (\ldots).$$

Substituting and setting $\alpha = \frac{1}{K}$, we obtain the bound.

Finite-time bound for the actors

Theorem 2: Finite-time bound for symmetric and asymmetric NAC.

For any $(\mathcal{Z}, U)$, we have for Algorithm 2 with $\alpha = \frac{1}{K}$, $\zeta = \frac{R\sqrt{1-\gamma}}{\sqrt{2N}}$, $\eta = \frac{1}{\sqrt{T}}$,

$$(1-\gamma) \min_{0 \leq t < T} \mathbb{E}[J(\pi^*) - J(\pi_t)] \leq \varepsilon_{\text{nac}} + \varepsilon_{\text{inf}} + \overline{C}_\infty \left(\varepsilon_{\text{actor}} + 2\varepsilon_{\text{grad}} + 2\sqrt{6}\frac{1}{T}\sum_{t=0}^{T-1} \varepsilon_{\text{critic}}^{\pi_t} \right),$$

$$\varepsilon_{\text{nac}} = \frac{R^2 + 2\log|A|}{2\sqrt{T}}$$

$$\varepsilon_{\text{actor}} = \sqrt{\frac{(2-\gamma)R}{(1-\gamma)\sqrt{N}}}$$

$$\varepsilon_{\text{inf,asym}} = 0 \qquad \varepsilon_{\text{inf,sym}} = 2\mathbb{E}^{\pi^*}\left[\sum_{k=0}^{\infty} \gamma^k \left\| \hat{b}_k - b_k \right\|_{\text{TV}}\right]$$

$$\varepsilon_{\text{grad,asym}} = \sup_{0 \leq t < T} \sqrt{\min_w \mathcal{L}_t(w)} \qquad \varepsilon_{\text{grad,sym}} = \sup_{0 \leq t < T} \sqrt{\min_w L_t(w)}$$

The term $\varepsilon_{\text{critic}}^{\pi_t}$ is given by Theorem 1, and $\sup_{0 \leq t < T} \mathbb{E}\left[\frac{d^{\pi^*}(S,Z,A)}{d^{\pi_t}(S,Z,A)}\right] \leq \overline{C}_\infty$.

Sketch of the actor proof

Let us first give the following performance difference lemma (Cayci et al., 2024),

$$V^{\pi^*}(z) - V^{\pi}(z) \leq \frac{1}{1-\gamma}\mathbb{E}^{d^{\pi^*}}[A^{\pi}(Z,A) \mid Z_0 = z] + \frac{2}{1-\gamma}\varepsilon_{\text{inf}}^{\pi^*}(z).$$

We start from the Lyapounov function $\Lambda(\pi) = \sum_z d^{\pi^*}(z)\ \mathrm{KL}(\pi^*(\cdot\,|z) \parallel \pi(\cdot\,|z))$, for which we can show, given than log-linear policies are 1-smooth,

$$\Lambda(\pi_{t+1}) - \Lambda(\pi_t) \leq \frac{\eta^2}{2}R^2 - \eta\sum_{z,a} d^{\pi^*}(z,a)A^{\pi}(z,a) + \eta\sum_{z,a} d^{\pi^*}(z,a)\sqrt{L(\bar{w}_t, z, a)}$$

After a few manipulation on $L(\bar{w}_t, z, a)$ by bounding $\|\bar{w} - w_*\|_2$ using SGD results for convex functions, we have using the lemma,

$$\Lambda(\pi_{t+1}) - \Lambda(\pi_t) \leq \frac{\eta^2}{2}R^2 - \eta(1-\gamma)\mathbb{E}[J(\pi^*) - J(\pi_t)] + 2\eta\varepsilon_{\text{inf}}^{\pi^*}(P)$$
$$+\eta\overline{C}_\infty\left(\sqrt{2}\varepsilon_{\text{actor}} + 2\varepsilon_{\text{grad}}^{\pi_t} + 2\sqrt{6}\varepsilon_{\text{critic}}^{\pi_t}\right)$$

By summing all Lyapounov drifts, rearranging, noting that $\Lambda(\pi_0) \leq \log|\mathcal{A}|$, and setting $\eta = \frac{1}{\sqrt{T}}$, we obtain the bound.

Some insights

When using an asymmetric actor-critic algorithm:

- The **critic error** has a **smaller upper bound**.
  - Because the asymmetric critic is the solution of a Bellman equation.
- The **actor suboptimality** has a **smaller upper bound**.
  - This benefit comes from the smaller upper bound on the critic error.

Some limitations:

- The analysis assumes a **fixed agent state process**.
  - Shed light on the effect of an aliased agent state (e.g., RNN at initialization).
  - It can easily be extended to learnable agent state processes: $\mathcal{A}^+ = \mathcal{A} \times \mathcal{Z}$.
- Requires **samples from the discounted visitation measure**.
  - But it is still feasible without assumption on the mixing time.
  - Reveal an interesting term $\varepsilon_{\text{shift}}$ when not assuming stationary distribution.

Conclusion

Take-home message

Don’t make the problem harder than it is.

Consider all available information at training.

Bonus: we start to see some theoretical justifications in the literature.

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