Refined Regret for Adversarial MDPs with Linear Function Approximation

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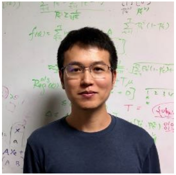
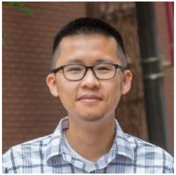
Yan Dai[1] Haipeng Luo[2] Chen-Yu Wei[3] Julian Zimmert[4]





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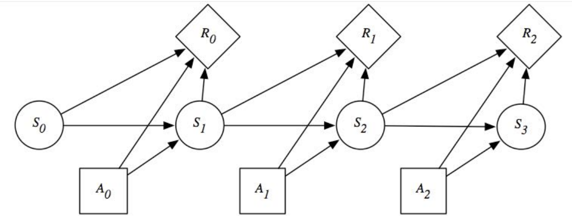
Adversarial Markov Decision Process (AMDP)

Algorithm Interaction Protocol in AMDP

for #episode $k = 1, 2, \ldots, K$ **do**
  Agent reset to an initial state $s_1 \in \mathcal{S}_1$ ▷ Let $\mathcal{S} = \mathcal{S}_1 \cup \mathcal{S}_2 \cup \cdots \cup \mathcal{S}_{H+1}$.
  for #step $h = 1, 2, \ldots, H$ **do**
    Agent picks an action $a_h \in \mathcal{A}$ ▷ Sample from **policy** $\pi_k : \mathcal{S} \to \triangle(\mathcal{A})$.
    Agent observes loss $\ell_{k,h}(s_h, a_h)$ ▷ **Loss ℓ depends on #episode k!**
    Agent transits to $s_{h+1} \sim \mathbb{P}(\cdot \mid s_h, a_h)$ ▷ Transition $\mathbb{P}$ independent to k.



Adversarial Markov Decision Process (AMDP)

Algorithm Interaction Protocol in AMDP

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for #episode k = 1, 2, ..., K do
    Agent reset to an initial state s_1 ∈ S_1          ▷ Let S = S_1 ∪ S_2 ∪ ··· ∪ S_{H+1}.
    for #step h = 1, 2, ..., H do
        Agent picks an action a_h ∈ A                  ▷ Sample from policy π_k : S → △(A).
        Agent observes loss ℓ_{k,h}(s_h, a_h)          ▷ Loss ℓ depends on #episode k!
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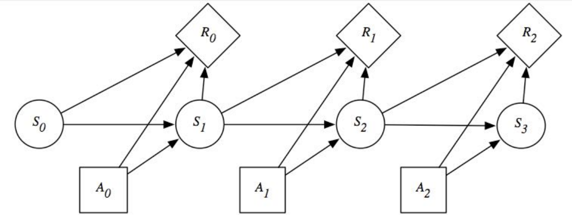

- Agent essentially decides K **policies** $\{\pi_k : \mathcal{S} \to \triangle(\mathcal{A})\}_{k=1}^{K}$.

Agent's Goal?

For the k-th episode, define **V-function** of policy $\pi\colon \mathcal{S} \to \triangle(\mathcal{A})$ as

$$V_k^\pi(s_1) = \mathbb{E}\left[\sum_{h=1}^{H} \ell_k(s_h, a_h) \middle| a_h \sim \pi_k(\cdot \mid s_h), s_{h+1} \sim \mathbb{P}(\cdot \mid s_h, a_h)\right].$$

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The agent minimizes the expected total loss $\mathbb{E}[\sum_{k=1}^K V_k^{\pi_k}(s_1)]$. Or equivalently, minimize the **total regret**:

$$\mathcal{R}_K \triangleq \mathbb{E}\left[\sum_{k=1}^{K} V_k^{\pi_k}(s_1)\right] - \min_{\pi^*\colon \mathcal{S}\to\triangle(\mathcal{A})} \left\{\sum_{k=1}^{K} V_k^{\pi^*}(s_1)\right\}.$$

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	Full Information	Bandit Feedback
Known Transition	$\widetilde{\mathcal{O}}(H\sqrt{\mathbf{K}})$ [Zimin and Neu, 2013]	$\widetilde{\mathcal{O}}(\sqrt{HSA}\sqrt{\mathbf{K}})$ [Zimin and Neu, 2013]
Unknown Transition	$\widetilde{\mathcal{O}}(HS\sqrt{A}\sqrt{\mathbf{K}})$ [Rosenberg and Mansour, 2019]	$\widetilde{\mathcal{O}}(HS\sqrt{A}\sqrt{\mathbf{K}})$ [Jin et al., 2020]

Table: Previous Results on AMDP (w/o Function Approximation)

(K: No. of episodes; H: No. of steps; S: Size of $\mathcal{S}$; A: Size of $\mathcal{A}$)

AMDP with Linear Function Approximation

What if $\mathcal{S}$ can be prohibitively large?

AMDP with Linear Function Approximation

What if $\mathcal{S}$ can be prohibitively large?
Linear-Q AMDP: $\forall k \in [K]$, $\pi \colon \mathcal{S} \to \triangle(\mathcal{A})$, $s \in \mathcal{S}$, $a \in \mathcal{A}$,

$$Q_k^\pi(s,a) \triangleq \ell_k(s,a) + \mathop{\mathbb{E}}_{s' \sim \mathbb{P}(\cdot|s,a),\ a' \sim \pi(\cdot|s')} \left[Q_k^\pi(s',a') \right] \text{ is linear,}$$

i.e., $Q_k^\pi(s,a) = \langle \phi(s,a), \theta_k^\pi \rangle$ where $\phi \colon \mathcal{S} \times \mathcal{A} \to \mathbb{R}^d$ is **known**.

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Some stronger variants of Linear-Q AMDP:

Linear MDP.	$\mathbb{P}(s' \mid s,a) = \langle \phi(s,a), \nu(s') \rangle$	(ϕ known but ν unknown).
Linear-Mixture MDP.	$\mathbb{P}(s' \mid s,a) = \langle \psi(s' \mid s,a), \nu \rangle$	(ψ known but ν unknown).
Linear Kernel MDP.	$\mathbb{P}(s' \mid s,a) = \langle \phi(s,a), M, \psi(s') \rangle$	(ϕ, ψ known but M unknown).

Previous Results on Linear-Q AMDPs

Setting	Assumption	Regret	
Linear-Q AMDP (with Simulator)	None	$\widetilde{\mathcal{O}}(d^{2/3}H^2\mathbf{K^{2/3}})$	[Luo et al., 2021a]
	Exploratory Policy	$\widetilde{\mathcal{O}}(\text{poly}(d,H)(\mathbf{K}/\lambda_0)^{1/2})$	[Luo et al., 2021a]
	None	$\widetilde{\mathcal{O}}(A^{1/2}d^{1/2}H^3\mathbf{K^{1/2}})$	(**This paper!**)
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(d: Dim. of ϕ; A: Size of $\mathcal{A}$; λ_0: Property of exploratory policy.)

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The first to get $\widetilde{\mathcal{O}}(\sqrt{K})$ regret w/o additional assumptions!

Previous Results on Other Variants

Setting	Assumption	Regret	
Linear-Mixture AMDP	**Full Information**	$\widetilde{\mathcal{O}}(dH\mathbf{K}^{1/2})$	[He et al., 2022]
	None	$\widetilde{\mathcal{O}}(d\mathbf{S}^2\mathbf{K}^{1/2}+\sqrt{H\mathbf{S}A}\mathbf{K}^{1/2})$	[Zhao et al., 2022]
Linear AMDP	**Known Transition**	$\widetilde{\mathcal{O}}(\text{poly}(d,H)(\mathbf{K}/\lambda_0)^{1/2})$	[Neu and Olkhovskaya, 2021]
	None	$\widetilde{\mathcal{O}}(d^2H^4\mathbf{K}^{14/15})$	[Luo et al., 2021b]
	Exploratory Policy	$\widetilde{\mathcal{O}}(\text{poly}(d,H)(\mathbf{K}/\lambda_0^{2/3})^{6/7})$	[Luo et al., 2021a]
	None	$\widetilde{\mathcal{O}}(\text{poly}(A,d,H)\mathbf{K}^{8/9})$	(**This paper!**)

Table: Previous Results on Other Variants of Linear-Q AMDPs.
(d: Dim. of ϕ; A: Size of $\mathcal{A}$; λ_0: Property of exploratory policy.)

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Greatly outperform previous works on Linear AMDPs!

Overview of Our Algorithms

3 Algorithms, 3 New Techniques.

1. **Algorithm 1**: $\widetilde{\mathcal{O}}(\sqrt{AdH^6K})$ in Linear-Q AMDPs
   - FTRL w/ Log-Barrier on **Arbitrary** Losses.
2. **Algorithm 2**: $\widetilde{\mathcal{O}}(\sqrt{\quad dH^6K})$ in Linear-Q AMDPs
   - Magnitude-Reduced Estimator for **Any** Random Variable.
3. **Algorithm 3**: $\widetilde{\mathcal{O}}(\text{poly}(A, d, H)K^{8/9})$ in Linear AMDPs:
   - **Relative Concentration** Bounds for Stochastic Matrices.

Recap of FTRL Framework

Follow-the-Regularized-Leader (FTRL) Framework: For any loss estimation sequence $\{\hat{\ell}_t\}_{t=1}^T$, calculate actions $\{x_t \in \triangle(\mathcal{A})\}_{t=1}^T$ as

$$x_t = \mathop{\arg\min}_{x \in \triangle(\mathcal{A})} \left\{ \eta \left\langle x, \sum_{\tau=1}^{t-1} \ell_\tau \right\rangle + \Psi(x) \right\}, \quad t = 1, 2, \ldots, T.$$

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Lemma (Classical Regret Guarantee on FTRL; Informal)

For "good enough" Ψ and ***losses such that*** $\hat{\ell}_{t,a} \geq -1/\eta$ ***for all*** $t = 1, 2, \ldots, T$ ***and*** $a \in \mathcal{A}$, *Eq. (1) holds for any fixed* $y \in \triangle(\mathcal{A})$.

$$\sum_{t=1}^T \langle x_t - y, \hat{\ell}_t \rangle \leq \frac{\Psi(y) - \Psi(x_1)}{\eta} + \eta \sum_{t=1}^T \sum_{a \in \mathcal{A}} x_{t,a} \hat{\ell}_{t,a}^2. \qquad (1)$$

What's the Issue?

In [Luo et al., 2021b], the final regret bound consists of

$$\widetilde{\mathcal{O}}\left(\beta K + \frac{1}{\eta} + \frac{\gamma}{\beta} K + \frac{\beta}{\gamma}\right),$$

where η is learning rate of FTRL, β is bonus coefficient, and γ is regularization factor (so the estimated loss $\hat{\ell} \in [-\gamma^{-1}, \gamma^{-1}]$).

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But... we also need $\hat{\ell} \geq -1/\eta = -\sqrt{K}$ to ensure Eq. (1).
So we essentially need $\gamma^{-1} \leq \eta^{-1}$ – that's why [Luo et al., 2021b] set $\beta = K^{-1/3}$, $\eta = K^{-2/3}$, $\gamma = K^{-2/3}$ for $\widetilde{\mathcal{O}}(K^{2/3})$ regret. ☹

How to Resolve?

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$$\sum_{t=1}^{T} \langle x_t - y, \hat{\ell}_t \rangle \le \frac{\Psi(y) - \Psi(x_1)}{\eta} + \eta \sum_{t=1}^{T} \sum_{a \in \mathcal{A}} x_{t,a} \hat{\ell}_{t,a}^2. \quad (1)$$

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Lemma (Our Regret Guarantee on FTRL; Informal)

*For **log-barrier** Ψ (defined as $\Psi(x) = \sum_{a \in \mathcal{A}} \ln x_a^{-1}$) and **any real loss vectors $\ell_1, \ell_2, \ldots, \hat{\ell}_t$**, Eq. (1) holds for any fixed $y \in \triangle(\mathcal{A})$.*

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In this way, we no longer need $\gamma^{-1} \le \eta^{-1}$ and get the **first-ever $\widetilde{\mathcal{O}}(K^{1/2})$ regret** via $\beta = K^{-1/2}$, $\eta = K^{-1/2}$, $\gamma = K^{-1/2}$! ☺

Downside of the Previous Approach?

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Can we still use the original lemma (to use negative-entropy Ψ and avoid poly(A)), but instead reducing the magnitude of $\hat{\ell}$? **Yes!**

Magnitude-Reduced Estimator for Any R.V.

Lemma (Magnitude-Reduced Estimator; Informal)

*For any random variable Z **unbounded from below**, the estimator*

$$\hat{Z} \triangleq Z - (Z)_- + \mathbb{E}[(Z)_-] \text{ where } (Z)_- \triangleq \min\{Z, 0\} \text{ ensures}$$

1. ***(Expectation Invariance)*** $\mathbb{E}[\hat{Z}] = \mathbb{E}[Z]$;
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Lemma

After applying the magnitude-reduced estimator to $\hat{\ell}$, the range of $\hat{\ell}$ moves from $[-\gamma^{-1}, \gamma^{-1}]$ to $[-\gamma^{-1/2}, \gamma^{-1}]$!

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$\Longrightarrow$ we only need $\gamma^{-1/2} \le \eta^{-1}$ instead of $\gamma^{-1} \le \eta^{-1}$!

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$\Longrightarrow$ we only need $\gamma^{-1/2} \leq \eta^{-1}$ instead of $\gamma^{-1} \leq \eta^{-1}$!
Still setting $\beta = K^{-1/2}$, $\eta = K^{-1/2}$, $\gamma = K^{-1/2}$ **gives $\widetilde{\mathcal{O}}(K^{1/2})$ regret & removes poly(A)** (as we use negative-entropy Ψ)! ☺

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- In Linear AMDPs, we get $\widetilde{\mathcal{O}}(K^{8/9})$ regret via a **new relative concentration bound** for stochastic matrices (in appendix).

Concluding Remarks

1. People now do better than our $\widetilde{\mathcal{O}}(K^{8/9})$ on Linear AMDPs:
   - Linear AMDP w/ Unknown Transition & Bandit Feedback **(our setup)**: $\widetilde{\mathcal{O}}(K^{6/7})$ [Sherman et al., 2023b] and $\widetilde{\mathcal{O}}(K^{4/5})$ [Kong et al., 2023] (requires the existence of an exploratory policy, but no polynomial dependency on λ_0 presents).

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    - Linear AMDP w/ Unknown Transition & Full Information **(weaker setup)**: $\widetilde{\mathcal{O}}(K^{1/2})$ [Sherman et al., 2023a].

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   - Linear AMDP w/ Unknown Transition & Full Information **(weaker setup)**: $\widetilde{\mathcal{O}}(K^{1/2})$ [Sherman et al., 2023a].
2. Our relative concentration result for stochastic matrices is further improved by [Liu et al., 2023] ($\widetilde{\mathcal{O}}(\gamma^{-2}) \Rightarrow \widetilde{\mathcal{O}}(\gamma^{-1})$).

Thank you for listening!

Questions are more than welcomed.

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Appendix. Our Relative Concentration Bound

Lemma (New Covariance Concentration; Informal)

For a d-dimensional distribution $\mathcal{D}$ w/ covariance Σ, sampling $W = (\mathbf{4d}\log\frac{\mathbf{d}}{\delta})\gamma^{\mathbf{-2}}$ i.i.d. samples $\phi_1, \phi_2, \ldots, \phi_W$ from $\mathcal{D}$ ensures

$$\left(\hat{\Sigma}^\dagger\right)^{1/2} (\gamma I + \Sigma) \left(\hat{\Sigma}^\dagger\right)^{1/2} \in [(\mathbf{1} - \mathbf{2}\sqrt{\gamma})\mathbf{I}, (\mathbf{1} + \mathbf{2}\sqrt{\gamma})\mathbf{I}],$$

where $\hat{\Sigma}^\dagger = \left(\gamma I + \sum_{w=1}^{W} \phi_w \phi_w^T\right)^{-1}$.

Previous approach gives **additive bounds**, e.g., Matrix Geometric Resampling (MGR) by [Neu and Olkhovskaya, 2020] needs $\mathcal{O}(\epsilon^{\mathbf{-2}}\gamma^{\mathbf{-3}})$ samples for a $\hat{\Sigma}^\dagger$ s.t. $\left\|\hat{\Sigma}^\dagger - (\gamma I + \Sigma)^{-1}\right\|_2 \le \epsilon$.