

Hi!

The Sample Complexity (with a Generative Model)

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CS 2824: Foundations of Reinforcement Learning

Announcements

- HW1 is posted now!
 - it cover many concepts from class
- Reading assignments
 - please do the readings; they are helpful for our lectures
 - next reading assignment posted soon

Today:

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- Recap: computational complexity
 - Question: Given an MDP $\mathcal{M} = (S, A, P, r, \gamma)$ can we **exactly compute** Q^\star (or find π^\star) in polynomial time?

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 - Question: Given an MDP $\mathcal{M} = (S, A, P, r, \gamma)$ can we **exactly compute** Q^\star (or find π^\star) in polynomial time?
- Today: **statistical complexity**
 - Question: Given only sampling access to an unknown MDP $\mathcal{M} = (S, A, P, r, \gamma)$ how many **observed transitions do we need to estimate** Q^\star (or find π^\star)?

Recap

Summary Table

	Value Iteration	Policy Iteration	LP-based Algorithms
Poly.	$S^2 A \frac{L(P,r,\gamma) \log \frac{1}{1-\gamma}}{1-\gamma}$	$(S^3 + S^2 A) \frac{L(P,r,\gamma) \log \frac{1}{1-\gamma}}{1-\gamma}$	$S^3 A L(P, r, \gamma)$
Strongly Poly.	X	$(S^3 + S^2 A) \cdot \min \left\{ \frac{A^S}{S}, \frac{S^2 A \log \frac{S^2}{1-\gamma}}{1-\gamma} \right\}$	$S^4 A^4 \log \frac{S}{1-\gamma}$

- VI: poly time for **fixed γ** , not strongly poly
- PI: poly and strongly-poly time for **fixed γ**
- LP approach: poly and strongly-poly time
(LP approach is only logarithmic in $1/(1 - \gamma)$)

Today

Sampling Models

(for learning in an unknown MDP)

w.p.r. $(1-\gamma)$ episode ends.

- **Episodic setting:**
 - in every episode, $s_0 \sim \mu$.
 - the learner acts for some finite number of steps and observes the trajectory.
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$$s' \sim P(\cdot | s, a)$$

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- You have a collection of observed transitions/reward: $\{(s, a, s', r(s, a))\}$
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 - input: (s, a) output: a sample $s' \sim P(\cdot | s, a)$ and $r(s, a)$
 - provides an “idealized model” to study statistical limits

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 - provides an “idealized model” to study statistical limits
- **Sample complexity of RL:**
how many transitions do we need observe in order to find a near optimal policy?

Two Fundamental Questions in Sample Complexity

$$P(s|s_a)$$

1. The Model Size Question (Sublinear Learning)

- How many parameters do we need to specify the transition kernel P ? $O(S^2A)$
(and how many for the policy?) $O(SA)$

- Q1: Can we find an ϵ -optimal policy with **sublinear** sample complexity?

$$\mathcal{O}(S^2A)$$

$$\mathcal{O}(SA)$$

fewer samples suffice?

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2. The Horizon Question (Error Amplification)

- The Scale: In discounted settings, the values scale as $1/(1 - \gamma)$.
- Target: It is natural to measure our additive error ϵ relative to this scale.
- Q2: What is the “**horizon amplification**”? i.e. the dependence on $1/(1 - \gamma)$

Attempt 1:

the naive model based approach

The most naive approach: model based

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- most naive approach to learning:
 - Call our simulator **N times at each state action pair.**
 - Let \hat{P} be our empirical model:

$$\hat{P}(s' | s, a) = \frac{\text{count}(s', s, a)}{N}$$

where $\text{count}(s', s, a)$ is the #times (s, a) transitions to state s' .

- we know the reward after one call.

(for simplicity, we often assume $r(s, a)$ is deterministic)

call to gen
model.
SA/N

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- we know the reward after one call.
(for simplicity, we often assume $r(s, a)$ is deterministic)
- The total number of calls to our generative model is **SAN** .

Model accuracy

Proposition: c is an absolute constant. $\epsilon > 0$. For $N \geq \frac{c\gamma}{(1-\gamma)^4} \frac{S \log(cSA/\delta)}{\epsilon^2}$
and with probability greater than $1 - \delta$,

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$$\|Q^\pi - \widehat{Q}^\pi\|_\infty \leq \epsilon / 2$$

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- Near optimal planning: Suppose that $\hat{\pi}^\star$ is the optimal policy in \widehat{M} .

$$\|Q^\star - Q^{\hat{\pi}^\star}\|_\infty \leq \epsilon$$

Matrix Expressions

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$$Q^\pi(s, \pi(s)) = V^\pi(s)$$

- With this notation,

$$Q^\pi = r + \gamma P V^\pi$$

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- Also,

$$Q^\pi = (I - \gamma P^\pi)^{-1} r$$

(where one can show the inverse exists)

“Simulation” Lemma

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Proof: Using our matrix equality for Q^π , we have:

$$\begin{aligned} Q^\pi - \widehat{Q}^\pi &= Q^\pi - (I - \gamma \widehat{P}^\pi)^{-1}r^\pi \\ &= (I - \gamma \widehat{P}^\pi)^{-1}((I - \gamma \widehat{P}^\pi) - (I - \gamma P^\pi))Q^\pi \\ &= \gamma(I - \gamma \widehat{P}^\pi)^{-1}(P^\pi - \widehat{P}^\pi)Q^\pi \\ &= \gamma(I - \gamma \widehat{P}^\pi)^{-1}(P - \widehat{P})V^\pi \end{aligned}$$

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- Concentration of a distribution in the ℓ_1 norm:
 - For a fixed s, a . With pr greater than $1 - \delta$,

$$\|P(\cdot | s, a) - \widehat{P}(\cdot | s, a)\|_1 \leq c \sqrt{\frac{S \log(1/\delta)}{N}}$$

with N samples used to estimate $\widehat{P}(\cdot | s, a)$.

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- The first claim now follows by the union bound.

Proof of Claim 2 (&3)

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For the second claim,

$$\|Q^\pi - \widehat{Q}^\pi\|_\infty = \|\gamma(I - \gamma \widehat{P}^\pi)^{-1}(P - \widehat{P})V^\pi\|_\infty$$

$$\begin{aligned} & \|(\mathbb{I} - \gamma P^\pi)^{-1}x\|_\infty \\ & \leq \underbrace{\frac{1}{1-\gamma}} \|x\|_\infty \end{aligned}$$

Proof of Claim 2 (&3)

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$$\begin{aligned}\|Q^\pi - \widehat{Q}^\pi\|_\infty &= \|\gamma(I - \gamma \widehat{P}^\pi)^{-1}(P - \widehat{P})V^\pi\|_\infty \\ &\leq \frac{\gamma}{1 - \gamma} \|(P - \widehat{P})V^\pi\|_\infty \\ &\leq \frac{\gamma}{1 - \gamma} \left(\max_{s,a} \|P(\cdot | s, a) - \widehat{P}(\cdot | s, a)\|_1 \right) \|V^\pi\|_\infty \\ &\leq \frac{\gamma}{(1 - \gamma)^2} \max_{s,a} \|P(\cdot | s, a) - \widehat{P}(\cdot | s, a)\|_1\end{aligned}$$

(why is the first inequality true?)

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The proof for the Claim 3 immediately follows from the second claim.

Attempt 2:

obtaining sublinear sample complexity

idea: use concentration only on V^\star

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- $\frac{1}{1-\gamma}(I - \gamma P^\pi)^{-1}$ is a matrix whose rows are probability distributions (why?)
- \widehat{Q}^* : optimal value in estimated model \widehat{M} .
 $\widehat{\pi}^*$: optimal policy in \widehat{M} .
 $Q^{\widehat{\pi}^*}$: (true) value of estimated policy.

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Proposition: (Crude Value Bound) With probability greater than $1 - \delta$,

$$\|Q^* - \widehat{Q}^*\|_\infty \leq \frac{\gamma}{(1 - \gamma)^2} \sqrt{\frac{2 \log(2SA/\delta)}{N}}$$

samples

SA/N

$$\|Q^* - \widehat{Q}^{\pi^*}\|_\infty \leq \frac{\gamma}{(1 - \gamma)^2} \sqrt{\frac{2 \log(2SA/\delta)}{N}}$$

Attempt 2: Sublinear Sample Complexity

$$Q^* = Q^{\pi^*}$$

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$$Q^* = Q^{\pi^*}$$

$$\|Q^* - \widehat{Q}^{\pi^*}\|_{\infty} \leq \frac{\gamma}{(1 - \gamma)^2} \sqrt{\frac{2 \log(2SA/\delta)}{N}}$$

What about the value of the policy?

$$\|Q^* - Q^{\widehat{\pi}^*}\|_{\infty} \leq \frac{\gamma}{(1 - \gamma)^3} \sqrt{\frac{2 \log(2SA/\delta)}{N}}$$

Sample Size Corollaries

Corollary: for $\epsilon < 1$, provided $N \geq \frac{c}{(1 - \gamma)^4} \frac{\log(cSA/\delta)}{\epsilon^2}$ then

$$\|Q^\star - \widehat{Q}^\star\|_\infty \leq \epsilon \text{ (with prob. greater than } 1 - \delta)$$

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What about the policy?

Corollary: for $\epsilon < 1$, provided $N \geq \frac{c}{(1-\gamma)^6} \frac{\log(cSA/\delta)}{\epsilon^2}$ then

$$\|Q^\star - Q^{\widehat{\pi}^\star}\|_\infty \leq \epsilon \text{ (with prob. greater than } 1 - \delta)$$

Component-wise Bounds Lemma

Lemma: we have that

$$Q^\star - \widehat{Q}^\star \leq \gamma(I - \gamma \widehat{P}^{\pi^\star})^{-1}(P - \widehat{P})V^\star$$

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$$\widehat{P} V^\star$$

Component-wise Bounds Lemma

$$\mathbb{E}_{s \sim \pi^* P(\cdot|s, a)} [V^*(s)] - \mathbb{E}_{s \sim \hat{P}(\cdot|s, a)} [V^*(s)]$$

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Proof:

For the first claim, the optimality of π^* in M implies:

$$Q^* - \hat{Q}^* = Q^{\pi^*} - \hat{Q}^{\hat{\pi}^*} \leq Q^{\pi^*} - \hat{Q}^{\pi^*} = \gamma(I - \gamma \hat{P}^{\pi^*})^{-1}(P - \hat{P})V^*,$$

using the simulation lemma in the final step.

See notes for the proof of second claim.

Proof: (& key idea for sublinearity)

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- Recall $\|V^\star\|_\infty \leq 1/(1-\gamma)$.

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- By Hoeffding's inequality and the union bound,

$$\begin{aligned} \|(P - \widehat{P})V^\star\|_\infty &= \max_{s,a} \left| E_{s' \sim P(\cdot|s,a)}[V^\star(s')] - E_{s' \sim \widehat{P}(\cdot|s,a)}[V^\star(s')] \right| \\ &\leq \frac{1}{1-\gamma} \sqrt{\frac{2 \log(2SA/\delta)}{N}} \end{aligned}$$

which holds with probability greater than $1 - \delta$.

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which holds with probability greater than $1 - \delta$.

- Proof of second claim is similar (see the book)

$$\frac{\text{Var}(f)}{\sqrt{n}}$$

$$E_{x \sim P}(f) - E[f] \leq \frac{\text{Bound}(f)}{\sqrt{n}}$$

$$\frac{\text{Var}(V^\star)}{\sqrt{N}}$$

Attempt 3:

minimax optimal sample complexity

idea: better variance control

(“near”) Minimax Optimal Sample Complexity

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Theorem: With probability greater than $1 - \delta$,

$$\|Q^* - \widehat{Q}^*\|_\infty \leq \gamma \sqrt{\frac{c}{(1-\gamma)^3} \frac{\log(cSA/\delta)}{N}} + \frac{c\gamma}{(1-\gamma)^3} \frac{\log(cSA/\delta)}{N},$$

where c is an absolute constant.

Minimax Optimal Sample Complexity

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Corollary: for $\epsilon < 1$, provided $N \geq \frac{c}{(1-\gamma)^3} \frac{\log(cSA/\delta)}{\epsilon^2}$ then

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What about the policy?

Naively, we need $N/(1 - \gamma)^2$ more samples.

A different thm gives: With the same N ,

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Lower Bound: We can't do better.

Revisiting proof attempt 2: where is there slop?

- **Proof of the first claim:**

- By comp. lemma: $\|Q^\star - \widehat{Q}^\star\|_\infty \leq \frac{\gamma}{1-\gamma} \|(P - \widehat{P})V^\star\|_\infty$

- Recall $\|V^\star\|_\infty \leq 1/(1-\gamma)$.

- By Hoeffding's inequality and the union bound,

$$\begin{aligned} \|(P - \widehat{P})V^\star\|_\infty &= \max_{s,a} \left| E_{s' \sim P(\cdot|s,a)}[V^\star(s')] - E_{s' \sim \widehat{P}(\cdot|s,a)}[V^\star(s')] \right| \\ &\leq \frac{1}{1-\gamma} \sqrt{\frac{2 \log(2SA/\delta)}{N}} \end{aligned}$$

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Proof sketch: part 1

- From Bernstein's ineq, with pr. greater than $1 - \delta$, we have (component-wise):

$$|(P - \hat{P})V^\star| \leq \sqrt{\frac{2 \log(2SA/\delta)}{N}} \sqrt{\text{Var}_P(V^\star)} + \frac{1}{1 - \gamma} \frac{2 \log(2SA/\delta)}{3N} \vec{1}$$

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- How to use this: again from “Component-wise Bounds” lemma,

$$Q^\star - \widehat{Q}^\star \leq \gamma \|(I - \gamma \widehat{P}^{\pi^\star})^{-1} (P - \widehat{P})V^\star\|_\infty \leq ??$$

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- How to use this: again from “Component-wise Bounds” lemma,

$$Q^* - \widehat{Q}^* \leq \gamma \|(I - \gamma \widehat{P}^{\pi^*})^{-1} (P - \widehat{P})V^*\|_\infty \leq ??$$

- Therefore

$$Q^* - \widehat{Q}^* \leq \gamma \sqrt{\frac{2 \log(2SA/\delta)}{N}} \|(I - \gamma \widehat{P}^{\pi^*})^{-1} \sqrt{\text{Var}_P(V^*)}\|_\infty \\ + \text{"lower order term"}$$

Bellman Equation for the (total) Variance

- **Variance:** $\text{Var}_P(V)(s, a) := \text{Var}_{P(\cdot|s,a)}(V)$

Component wise variance: $\text{Var}_P(V) := P(V)^2 - (PV)^2$

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- Let's keep around the MDP M subscripts.

Define Σ_M^π as the (total) variance of the discounted reward:

$$\Sigma_M^\pi(s, a) := E \left[\left(\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) - Q_M^\pi(s, a) \right)^2 \middle| s_0 = s, a_0 = a \right]$$

Bellman Equation for the (total) Variance

- **Variance:** $\text{Var}_P(V)(s, a) := \text{Var}_{P(\cdot|s,a)}(V)$

Component wise variance: $\text{Var}_P(V) := P(V)^2 - (PV)^2$

- Let's keep around the MDP M subscripts.

Define Σ_M^π as the (total) variance of the discounted reward:

$$\Sigma_M^\pi(s, a) := E \left[\left(\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) - Q_M^\pi(s, a) \right)^2 \middle| s_0 = s, a_0 = a \right]$$

- **Bellman equation for the total variance:**

$$\Sigma_M^\pi = \gamma^2 \text{Var}_P(V_M^\pi) + \gamma^2 P^\pi \Sigma_M^\pi$$

Key Lemma

Lemma: For any policy π and MDP M ,

$$\left\| (I - \gamma P^\pi)^{-1} \sqrt{\text{Var}_P(V_M^\pi)} \right\|_\infty \leq \sqrt{\frac{2}{(1 - \gamma)^3}}$$

Proof idea: convexity + Bellman equations for the variance.

Putting it all together

Proof sketch: we have two MDPs M and \hat{M} . need to bound:

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First equality above: just notation

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Second step: concentration \rightarrow we need to quantify:

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Last step: previous slide