Policy Gradient: Optimality

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CS 6789: Foundations of Reinforcement Learning

Today

- Recap
- Today:
  - NPG convergence proof wrap up
  - What about function approximation?
    remember compatible function approximation
    log linear policy classes and neural policy classes

- PG methods have stronger guarantees (over approximate value function methods) when we have errors.

Recap

Things to remember

For all π, π', s_0:

$$V^{\pi}(s_0) - V^{\pi'}(s_0) = \frac{1}{1-\gamma}\mathbb{E}_{s\sim d^{\pi}_{s_0}}\mathbb{E}_{a\sim\pi(\cdot|s)}\left[A^{\pi'}(s,a)\right]$$

$A^{\pi_\theta}(s,a)$

$\updownarrow$

$$\nabla_\theta J(\theta) := \frac{1}{1-\gamma}\mathbb{E}_{s,a\sim d^{\pi_\theta}}\left[\nabla_\theta \ln \pi_\theta(a\,|\,s) Q^{\pi_\theta}(s,a)\right]$$

Today: we will use $d^{\pi}_{s_0}$ for a state distribution measure.

(it should be clear from context how we use it).

$\geq (1-\gamma)\Pr(s_0 = s) = (1-\gamma)\mu(s)$

$$d^{\pi}_{s_0}(s) = (1-\gamma)\sum_{h=0}^{\infty}\gamma^h \mathbb{P}(s_h = s\,|\,s_0, \pi)$$

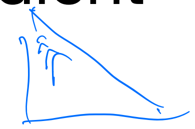
μ

$$d^{\pi}_{s_0}(s,a) = (1-\gamma)\sum_{h=0}^{\infty}\gamma^h \mathbb{P}(s_h = s, a_h = a\,|\,s_0, \pi)$$

$$V^{\pi}(\mu) = E_{s\sim\mu}[V^{\pi}(s)]$$

$$d^{\pi}_{\mu}(s) = E_{s_0\sim\mu}[d^{\pi}_{s_0}(s)]$$

The Natural Policy Gradient



- Recall that the Fisher information matrix of a parameterized density $p_\theta(x)$ is defined as $E_{x \sim p_\theta}\left[\nabla \log p_\theta(x) \nabla \log p_\theta(x)^\top\right]$
- Define $\mathcal{F}_\rho^\theta$ as the (average) Fisher matrix on the family of distributions $\{\pi_\theta(\cdot \mid s) \mid s \in S\}$ as: $\mathcal{F}_\rho^\theta := E_{s \sim d_\rho^{\pi_\theta}} E_{a \sim \pi_\theta(\cdot \mid s)}\left[(\nabla \log \pi_\theta(a \mid s)) \nabla \log \pi_\theta(a \mid s)^\top\right]$.
- The NPG algorithm performs gradient updates in this induced geometry: $\theta^{(t+1)} = \theta^{(t)} + \eta F_\rho(\theta^{(t)})^\dagger \nabla_\theta V^{(t)}(\rho),$

  where $M^\dagger$ denotes the Moore-Penrose pseudoinverse of M.

PSD

Compatible Function Approximation

- Let $w^\star$ denote the following minimizer of the "compatible function approximation" error:

$$w^\star \in \text{argmin}_w E_{s\sim d_\mu^{\pi_\theta}} E_{a\sim\pi_\theta(\cdot|s)} \left[\left(A^{\pi_\theta}(s,a) - w \cdot \nabla_\theta \log \pi_\theta(a|s) \right)^2 \right]$$

- Lemma: Let $\widehat{A}^{\pi_\theta}(s,a)$ be the best linear predictor of $A^{\pi_\theta}(s,a)$ using $\nabla_\theta \log \pi_\theta(a|s)$, i.e. $\widehat{A}^{\pi_\theta}(s,a) := w^\star \cdot \nabla_\theta \log \pi_\theta(a|s)$. We have:

$$\nabla_\theta V^{\pi_\theta}(\mu) = \frac{1}{1-\gamma} E_{s\sim d_\mu^{\pi_\theta}} E_{a\sim\pi_\theta(\cdot|s)} \left[\nabla_\theta \log \pi_\theta(a|s) \widehat{A}^{\pi_\theta}(s,a) \right]$$

We can use $\widehat{A}^{\pi_\theta}(s,a)$ instead of $A^{\pi_\theta}(s,a)$.

$$\theta \leftarrow \theta + \frac{\eta}{1-\gamma} w^\star(\theta)$$

- Lemma: We have that $F_\mu(\theta)^\dagger \nabla_\theta V^\theta(\mu) = \frac{1}{1-\gamma} w^\star$,

The NPG direction is the weights $w^\star$

NPG softmax case

(NPG as "soft" policy iteration)

Vanilla PG $\theta \leftarrow \theta + \frac{\eta}{1-\gamma} d_\mu^\theta(s)\, \pi^\theta(a|s)\, A^\theta(s,a)$

- Lemma: (Softmax NPG as soft policy iteration) The NPG update is:

$$\theta^{(t+1)} = \theta^{(t)} + \frac{\eta}{1-\gamma} A^{(t)}$$

- and this leads to the update:

$$\pi^{(t+1)}(a \mid s) = \pi^{(t)}(a \mid s) \frac{\exp\left(\eta A^{(t)}(s,a)/(1-\gamma)\right)}{Z_t(s)},$$

where $Z_t(s) = \sum_a \pi^{(t)}(a \mid s) \exp\left(\eta A^{(t)}(s,a)/(1-\gamma)\right)$.

Today:

Natural Policy Gradient:
Global Convergence and Function Approximation

Global convergence for Softmax NPG

- Theorem: Params: $\theta^{(0)} = 0$ and $\eta > 0$. For all ρ and $T > 0$, we have:
$$V^{(T)}(\rho) \geq V^{\star}(\rho) - \frac{\log A}{\eta T} - \frac{1}{(1-\gamma)^2 T}\,.$$

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- Setting $\eta \geq (1-\gamma)^2 \log A$, NPG finds an ϵ-opt policy when $T \geq \dfrac{2}{(1-\gamma)^2 \epsilon}$.
- Iteration complexity has:
  - No dimension dependence (no dependence on S, A)
  - No dependence on start state measure ρ (and no “dist mismatch factor”)
  - No ‘flat gradient’ problem
- + “fast rate” (not $\frac{1}{\sqrt{T}}$)

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  - No 'flat gradient' problem
- What about approx/estimation errors? ~~(next lecture)~~

Improvement Lower Bound

- Lemma: For the iterates $\pi^{(t)}$ generated by the NPG, we have for all distributions μ:

$$V^{(t+1)}(\mu) - V^{(t)}(\mu) \geq \frac{(1-\gamma)}{\eta} E_{s\sim\mu} \log Z_t(s) \geq 0.$$

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- Proof: First, let us show that $\log Z_t(s) \geq 0$. To see this, observe:

$$\log Z_t(s) = \log \sum_a \pi^{(t)}(a \mid s) \exp(\eta A^{(t)}(s,a)/(1-\gamma))$$

$$\geq \sum_a \pi^{(t)}(a \mid s) \log \exp(\eta A^{(t)}(s,a)/(1-\gamma))$$

$$= \frac{\eta}{1-\gamma} \sum_a \pi^{(t)}(a \mid s) A^{(t)}(s,a) = 0.$$

(using Jensen's inequality on the concave function $\log x$.)

Lemma Proof: continued….

By the performance difference lemma,

$$V^{(t+1)}(\mu) - V^{(t)}(\mu) = \frac{1}{1-\gamma} E_{s\sim d_\mu^{(t+1)}} \sum_a \pi^{(t+1)}(a\,|\,s) A^{(t)}(s,a)$$

$$= \frac{1}{\eta} E_{s\sim d_\mu^{(t+1)}} \sum_a \pi^{(t+1)}(a\,|\,s) \log \frac{\pi^{(t+1)}(a\,|\,s) Z_t(s)}{\pi^{(t)}(a\,|\,s)}$$

$$= \frac{1}{\eta} E_{s\sim d_\mu^{(t+1)}} \mathrm{KL}(\pi_s^{(t+1)} \,||\, \pi_s^{(t)}) + \frac{1}{\eta} E_{s\sim d_\mu^{(t+1)}} \log Z_t(s)$$

$$\geq \frac{1}{\eta} E_{s\sim d_\mu^{(t+1)}} \log Z_t(s) \geq \frac{1-\gamma}{\eta} E_{s\sim\mu} \log Z_t(s),$$

where the last step uses that $d_\mu^{(t+1)} \geq (1-\gamma)\mu$ and that $\log Z_t(s) \geq 0$.

from the NPG softmax

$A^t(s,a) = \frac{1-\gamma}{\eta} \log \frac{\pi^{t+1}(a|s) Z^t(s)}{\pi^t(a|s)}$

rearranging + $\sum_a \pi^{t+1}(a|s) = 1$

KL ≥ 0

NPG Conv. Proof, Part 1

- $d^\star$ as shorthand for $d_\rho^\star$; π_s as shorthand for the vector of $\pi(\cdot \mid s)$

NPG Conv. Proof, Part 1

- $d^\star$ as shorthand for $d^\star_\rho$; π_s as shorthand for the vector of $\pi(\cdot \mid s)$
- By the performance difference lemma,

$$V^{\pi^\star}(\rho) - V^{(t)}(\rho) = \frac{1}{1-\gamma} E_{s\sim d^\star_\rho} \sum_a \pi^\star(a \mid s) A^{(t)}(s,a)$$

by the NPG softmax rule.

$$= \frac{1}{\eta} E_{s\sim d^\star} \sum_a \pi^\star(a \mid s) \log \frac{\pi^{(t+1)}(a \mid s) Z_t(s)}{\pi^{(t)}(a \mid s)}$$

by KL def.

$$= \frac{1}{\eta} E_{s\sim d^\star} \left(\mathrm{KL}(\pi_s^\star \,||\, \pi_s^{(t)}) - \mathrm{KL}(\pi_s^\star \,||\, \pi_s^{(t+1)}) + \sum_a \pi^*(a \mid s) \log Z_t(s) \right)$$

$\sum_a \pi^*(a|s) f(s) = f(s)$

$$= \frac{1}{\eta} E_{s\sim d^\star} \left(\mathrm{KL}(\pi_s^\star \,||\, \pi_s^{(t)}) - \mathrm{KL}(\pi_s^\star \,||\, \pi_s^{(t+1)}) + \log Z_t(s) \right),$$

NPG Conv. Proof, Part 2

- By the improvement lemma $V^{(t+1)}(\rho) \geq V^{(t)}(\rho)$. Hence,

$$V^{\pi^\star}(\rho) - V^{(T-1)}(\rho) \leq \frac{1}{T}\sum_{t=0}^{T-1}(V^{\pi^\star}(\rho) - V^{(t)}(\rho))$$

by prev. equality

$$= \frac{1}{\eta T}\sum_{t=0}^{T-1} E_{s\sim d^\star}(\mathrm{KL}(\pi_s^\star || \pi_s^{(t)}) - \mathrm{KL}(\pi_s^\star || \pi_s^{(t+1)})) + \frac{1}{\eta T}\sum_{t=0}^{T-1} E_{s\sim d^\star} \log Z_t(s)$$

$$\leq \frac{E_{s\sim d^\star}\mathrm{KL}(\pi_s^\star || \pi^{(0)})}{\eta T} + \frac{1}{\eta T}\sum_{t=0}^{T-1} E_{s\sim d^\star} \log Z_t(s) .$$

by telescoping + $KL^{T-1} > 0$

(Aside:)

$$Z_t = \sum_a \pi_t(a|s) e^{\eta A^t(s,a)}$$

$$\approx 1 + \eta \cdot 0 + O(\eta^2).$$

$\log Z_t \approx O(\eta^2).$

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- By the improvement lemma $V^{(t+1)}(\rho) \geq V^{(t)}(\rho)$. Hence,

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$$= \frac{1}{\eta T} \sum_{t=0}^{T-1} E_{s\sim d^\star}(\mathrm{KL}(\pi_s^\star || \pi_s^{(t)}) - \mathrm{KL}(\pi_s^\star || \pi_s^{(t+1)})) + \frac{1}{\eta T} \sum_{t=0}^{T-1} E_{s\sim d^\star} \log Z_t(s)$$

$$\leq \frac{E_{s\sim d^\star} \mathrm{KL}(\pi_s^\star || \pi^{(0)})}{\eta T} + \frac{1}{\eta T} \sum_{t=0}^{T-1} E_{s\sim d^\star} \log Z_t(s) \,.$$

- By the improvement lemma (applied with $d^\star$ as the distribution), we have:

$$\frac{1}{\eta} E_{s\sim d^\star} \log Z_t(s) \leq \frac{1}{1-\gamma} \left(V^{(t+1)}(d^\star) - V^{(t)}(d^\star) \right)$$

which gives us a bound on $E_{s\sim d^\star} \log Z_t(s)$.

NPG Conv. Proof, Part 3

$$V^{\pi^\star}(\rho) - V^{(T-1)}(\rho) \le \frac{E_{s\sim d^\star}\mathrm{KL}(\pi_s^\star \,||\, \pi^{(0)})}{\eta T} + \frac{1}{\eta T}\sum_{t=0}^{T-1} E_{s\sim d^\star} \log Z_t(s)$$

$$\le \frac{E_{s\sim d^\star}\mathrm{KL}(\pi_s^\star \,||\, \pi^{(0)})}{\eta T} + \frac{1}{(1-\gamma)T}\sum_{t=0}^{T-1}\Big(V^{(t+1)}(d^\star) - V^{(t)}(d^\star)\Big)$$

$$= \frac{E_{s\sim d^\star}\mathrm{KL}(\pi_s^\star \,||\, \pi^{(0)})}{\eta T} + \frac{V^{(T)}(d^\star) - V^{(0)}(d^\star)}{(1-\gamma)T}$$

$$\le \frac{\log A}{\eta T} + \frac{1}{(1-\gamma)^2 T}.$$

prev. page

imp. lemma with $\mu = d^*$

telescoping

$V(s) \le \frac{1}{1-\gamma}$

What about Function Approximation?

+ estimation error

NPG and variants for log-linear policy classes

What about Function Approximation?

1. Softmax Policy for Tabular MDPs:

$$\theta_{s,a} \in \mathbb{R}, \forall s, a \in S \times A$$

$$\pi_\theta(a \mid s) = \frac{\exp(\theta_{s,a})}{\sum_{a'} \exp(\theta_{s,a'})}$$

2. Log Linear Policy (e.g., for linear MDPs):

Feature vector $\phi(s, a) \in \mathbb{R}^d$, and parameter $\theta \in \mathbb{R}^d$

$$\pi_\theta(a \mid s) = \frac{\exp(\theta^\top \phi(s, a))}{\sum_{a'} \exp(\theta^\top \phi(s, a'))}$$

3. Neural Policy:

Neural network $f_\theta : S \times A \mapsto \mathbb{R}$

$$\pi_\theta(a \mid s) = \frac{\exp(f_\theta(s, a))}{\sum_{a'} \exp(f_\theta(s, a'))}$$

NPG & Log Linear Policy Classes

- Feature vector $\phi(s, a) \in \mathbb{R}^d$, $\pi_\theta(a \mid s) = \dfrac{\exp(\theta^\top \phi(s, a))}{\sum_{a'} \exp(\theta^\top \phi(s, a'))}$

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- We have:
  $\nabla_\theta \log \pi_\theta(a \mid s) = \overline{\phi}^\theta_{s,a}$, where $\overline{\phi}^\theta_{s,a} = \phi_{s,a} - E_{a' \sim \pi_\theta(\cdot \mid s)}[\phi_{s,a'}]$.

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- The NPG update:
  $\theta \leftarrow \theta + \eta w_\star$, $\qquad w_\star \in \text{argmin}_w E_{s \sim d_\rho^{\pi_\theta}, a \sim \pi_\theta(\cdot \mid s)}\left[\left(A^{\pi_\theta}(s,a) - w \cdot \overline{\phi}^{\theta}_{s,a}\right)^2\right]$.

  $1-\gamma$

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- Equivalently, for the same $w_\star$,
  $$\pi(a \mid s) \leftarrow \frac{\pi(a \mid s) \exp(w_\star \cdot \phi_{s,a})}{Z_s}$$

  $\cdot \frac{\eta}{1-\gamma}$ $\qquad \hat{A}^{\theta}_{s,a} := w^\star \cdot \overline{\phi}_{s,a}$.

  (Z_s is the normalizing constant.) Using $\overline{\phi}$ or ϕ result in the same update for π.

Q-NPG: use Q rather A

(a little nice to interpret for analysis)

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Approximate Q-NPG + With a Starting Measure

(e.g. we use samples to estimate Q)

- For a state-action distribution D, define:
  $L(w;\theta,D) := E_{s,a\sim D}\left[(Q^{\pi_\theta}(s,a) - w\cdot\phi_{s,a})^2\right]$.

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- Let us consider using an on-policy state action measure starting with $s_0, a_0 \sim \nu$.
  - this will help with "exploration" and the flat gradient problem when there is approximation
  - shorthand:
    $d^{(t)}(s,a) := d_\nu^{\pi^{(t)}}(s,a)$

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- The approximate version:
  $\theta^{(t+1)} = \theta^{(t)} + \eta w^{(t)}$, where. $w^{(t)} \approx \text{argmin}_{\|w\|_2\le W} L(w;\theta^{(t)}, d^{(t)})$,

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Generic Perturbation Analysis of NPG

NPG regret lemma

- Set $\theta^{(0)} = 0$. Consider an arbitrary sequence of weights $w^{(0)}, \ldots, w^{(T)}$, s.t. $\|w^{(t)}\|_2 \leq W$.

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- Lemma: (NPG Regret Lemma)
  Fix any comparison policy $\widetilde{\pi}$ and any state distribution ρ.
  Assume $\log \pi_\theta(a \mid s)$ (for all s, a) is a β-smooth function of θ.
  Define: $\mathrm{err}_t = E_{s \sim \widetilde{d}} E_{a \sim \widetilde{\pi}(\cdot \mid s)} \left[A^{(t)}(s,a) - w^{(t)} \cdot \nabla_\theta \log \pi^{(t)}(a \mid s) \right]$.
  We have that:

$$\min_{t<T} \left\{ V^{\widetilde{\pi}}(\rho) - V^{(t)}(\rho) \right\} \leq \frac{1}{1-\gamma} \left(W \sqrt{\frac{2\beta \log A}{T}} + \frac{1}{T} \sum_{t=0}^{T-1} \mathrm{err}_t \right).$$

(where we set using $\eta = \sqrt{2 \log A / (\beta W^2 T)}$)

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  (where we set using $\eta = \sqrt{2 \log A / (\beta W^2 T)}$)

- Proof: Mirror descent style of analysis + Perf. Difference Lemma

Approximate Q-NPG

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- Error Decomposition:

$$L(w^{(t)}; \theta^{(t)}, d^{(t)}) = \underbrace{L(w^{(t)}; \theta^{(t)}, d^{(t)}) - L(w_\star^{(t)}; \theta^{(t)}, d^{(t)})}_{\text{Excess risk}} + \underbrace{L(w_\star^{(t)}; \theta^{(t)}, d^{(t)})}_{\text{Approximation error}}$$

where $w_\star^{(t)} \in \text{argmin}_{\|w\|_2 \le W} L(w; \theta^{(t)}, d^{(t)})$

Q-NPG Conv Rate w/ Estimation Error (no approx error)

- Suppose no approx error: $L(w_\star^{(t)}; \theta^{(t)}, d^{(t)}) = 0$

  Suppose the excess risk:

  $L(w^{(t)}; \theta^{(t)}, d^{(t)}) - L(w_\star^{(t)}; \theta^{(t)}, d^{(t)}) \leq \epsilon_{\text{stat}}$,

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  Suppose the excess risk:
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- Conditioning: suppose $\|\phi_{s,a}\|_2 \leq 1$ and, for the initial measure ν,
  $\sigma_{\min}\left(E_{s,a\sim\nu}\left[\phi_{s,a}\phi_{s,a}^\top\right]\right) = \lambda_{\min}, \quad \kappa = 1/\lambda\,.$

Q-NPG Conv Rate w/ Estimation Error (no approx error)

- Suppose no approx error: $L(w_\star^{(t)}; \theta^{(t)}, d^{(t)}) = 0$

  Suppose the excess risk:

  $L(w^{(t)}; \theta^{(t)}, d^{(t)}) - L(w_\star^{(t)}; \theta^{(t)}, d^{(t)}) \le \epsilon_{\text{stat}}$,

- Conditioning: suppose $\|\phi_{s,a}\|_2 \le 1$ and, for the initial measure ν,

  $\sigma_{\min}\left(E_{s,a\sim\nu}\left[\phi_{s,a}\phi_{s,a}^\top\right]\right) = \lambda_{\min}, \quad \kappa = 1/\lambda\,.$

- Theorem: Fix any state distribution ρ; any comparator policy $\pi^\star$ (not necessarily optimal).

  With η set appropriately and under the above assumptions, we have that:

$$E\left[\min_{t<T}\left\{V^{\pi^\star}(\rho) - V^{(t)}(\rho)\right\}\right] \le \frac{W}{1-\gamma}\sqrt{\frac{2\log A}{T}} + \sqrt{\frac{4A}{(1-\gamma)^3}\left(\kappa \cdot \epsilon_{\text{stat}}\right)}$$

Q-NPG Conv Rate with Approx+Est. Errors

- Suppose the excess risk and approx error are bounded as:

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NPG & Neural Policy Classes

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$$\pi_\theta(a \mid s) = \frac{\exp(f_\theta(s, a))}{\sum_{a'} \exp(f_\theta(s, a'))}$$

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