Lecture 8: Policy Gradient I [2]

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CS234 Reinforcement Learning.

Winter 2018

- Additional reading: Sutton and Barto 2018 Chp. 13

[2] With many slides from or derived from David Silver and John Schulman and Pieter Abbeel

Class Feedback

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- Of 70 responses, 54% thought too fast, 43% just right
- Multiple request to: repeat questions for those watching later on; have more worked examples; have more conceptual emphasis; minimize notation errors
- Common things people find are helping them learn: assignments, mathematical derivations, checking your understanding/talking to a neighbor

Class Structure

- Last time: Policy Search
- **This time: Policy Search**
- Next time: Midterm review

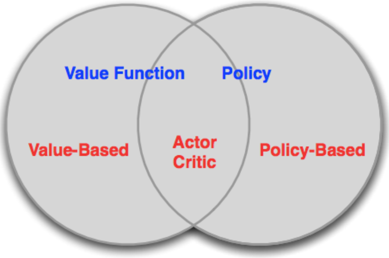
Recall: Policy-Based RL

poor policy parameteriz.
how well do we do search

- Policy search: directly parametrize the policy

$$\pi_\theta(s, a) = \mathbb{P}[a|s, \theta]$$

- Goal is to find a policy π with the highest value function V^π
- (Pure) Policy based methods
  - No Value Function
  - Learnt Policy
- Actor-Critic methods
  - Learnt Value Function
  - Learnt Policy



Recall: Advantages of Policy-Based RL

Advantages:

- Better convergence properties
- Effective in high-dimensional or continuous action spaces
- Can learn stochastic policies

Disadvantages:

- Typically converge to a local rather than global optimum
- Evaluating a policy is typically inefficient and high variance

Recall: Policy Gradient

- Defined $V(\theta) = V^{\pi_\theta}$ to make explicit the dependence of the value on the policy parameters
- Assumed episodic MDPs
- Policy gradient algorithms search for a *local* maximum in $V(\theta)$ by ascending the gradient of the policy, w.r.t parameters θ

$$\nabla\theta = \alpha \nabla_\theta V(\theta)$$

- Where $\nabla_\theta V(\theta)$ is the policy gradient

$$\nabla_\theta V(\theta) = \begin{pmatrix} \frac{\delta V(\theta)}{\delta \theta_1} \\ \vdots \\ \frac{\delta V(\theta)}{\delta \theta_n} \end{pmatrix}$$

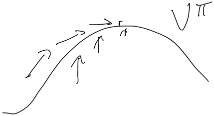
- and α is a step-size parameter

Desiblue Properties of a Policy Gradient RL Algorithm

- Goal: Converge as quickly as possible to a local optima
  - Incurring reward / cost as execute policy, so want to minimize number of iterations / time steps until reach a good policy

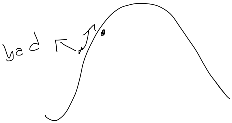
Desiblue Properties of a Policy Gradient RL Algorithm

- Goal: Converge as quickly as possible to a local optima
  - Incurring reward / cost as execute policy, so want to minimize number of iterations / time steps until reach a good policy
- During policy search alternating between evaluating policy and changing (improving) policy (just like in policy iteration)
- Would like each policy update to be a monotonic improvement
  - Only guaranteed to reach a local optima with gradient descent
  - Monotonic improvement will achieve this
  - And in the real world, monotonic improvement is often beneficial



Desiblue Properties of a Policy Gradient RL Algorithm

- Goal: Obtain large monotonic improvements to policy at each update
- Techniques to try to achieve this:
  - Last time and today: Get a better estimate of the gradient (intuition: should improve updating policy parameters)
  - Today: Change how to update the policy parameters given the gradient



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Likelihood Ratio / Score Function Policy Gradient

- Recall last time: m is a set of traj

$$\nabla_\theta V(\theta) \approx (1/m) \sum_{i=1}^{m} R(\tau^{(i)}) \sum_{t=0}^{T-1} \nabla_\theta \log \pi_\theta(a_t^{(i)} | s_t^{(i)})$$

- Unbiased estimate of gradient but very noisy
- Fixes that can make it practical
  - Temporal structure (discussed last time)
  - Baseline
  - Alternatives to using Monte Carlo returns $R * \tau^{(i)}$ as targets

Policy Gradient: Introduce Baseline

Red

- ~~blu~~euce variance by introducing a *baseline* $b(s)$

$$\nabla_\theta \mathbb{E}_\tau[R] = \mathbb{E}_\tau \left[\sum_{t=0}^{T-1} \nabla_\theta \log \pi(a_t|s_t, \theta) \left(\sum_{t'=t}^{T-1} r_{t'} - b(s_t) \right) \right]$$

- For any choice of b, gradient estimator is unbiased.
- Near optimal choice is expected return, $b(s_t) \approx \mathbb{E}[r_t + r_{t+1} + \cdots + r_{T-1}]$
- Interpretation: increase logprob of action a_t proportionally to how much returns $\sum_{t'=t}^{T-1} r_{t'}$ are better than expected

Baseline $b(s)$ Does Not Introduce Bias–Derivation

$$\mathbb{E}_\tau[\nabla_\theta \log \pi(a_t|s_t,\theta)b(s_t)]$$
$$= \mathbb{E}_{s_{0:t},a_{0:(t-1)}}\left[\mathbb{E}_{s_{(t+1):T},a_{t:(T-1)}}[\nabla_\theta \log \pi(a_t|s_t,\theta)b(s_t)]\right]$$

Baseline $b(s)$ Does Not Introduce Bias–Derivation

$$
\begin{aligned}
&\mathbb{E}_\tau[\nabla_\theta \log \pi(a_t|s_t,\theta) b(s_t)] \\
&= \mathbb{E}_{s_{0:t},a_{0:(t-1)}}\left[\mathbb{E}_{s_{(t+1):T},a_{t:(T-1)}}[\nabla_\theta \log \pi(a_t|s_t,\theta) b(s_t)]\right] \text{ (break up expectation)} \\
&= \mathbb{E}_{s_{0:t},a_{0:(t-1)}}\left[b(s_t)\mathbb{E}_{s_{(t+1):T},a_{t:(T-1)}}[\nabla_\theta \log \pi(a_t|s_t,\theta)]\right] \text{ (pull baseline term out)} \\
&= \mathbb{E}_{s_{0:t},a_{0:(t-1)}}[b(s_t)\mathbb{E}_{a_t}[\nabla_\theta \log \pi(a_t|s_t,\theta)]] \text{ (remove irrelevant variables)} \quad \checkmark \\
&= \mathbb{E}_{s_{0:t},a_{0:(t-1)}}\left[b(s_t)\sum_a \pi_\theta(a_t|s_t)\frac{\nabla_\theta\pi(a_t|s_t,\theta)}{\pi_\theta(a_t|s_t)}\right] \text{ (likelihood ratio)} \\
&= \mathbb{E}_{s_{0:t},a_{0:(t-1)}}\left[b(s_t)\sum_a \nabla_\theta\pi(a_t|s_t,\theta)\right] \\
&= \mathbb{E}_{s_{0:t},a_{0:(t-1)}}\left[b(s_t)\nabla_\theta\sum_a \pi(a_t|s_t,\theta)\right] \quad \checkmark \\
&= \mathbb{E}_{s_{0:t},a_{0:(t-1)}}[b(s_t)\nabla_\theta 1] \\
&= \mathbb{E}_{s_0:t,a_0:(t-1)}[b(s_t)\cdot 0] = 0
\end{aligned}
$$

"Vanilla" Policy Gradient Algorithm

Initialize policy parameter θ, baseline b
for iteration$=1, 2, \cdots$ **do**
  Collect a set of trajectories by executing the current policy
  At each timestep in each trajectory, compute
    the *return* $R_t = \sum_{t'=t}^{T-1} r_{t'}$, and
    the *advantage estimate* $\hat{A}_t = R_t - b(s_t)$.
  Re-fit the baseline, by minimizing $||b(s_t) - R_t||^2$,
    summed over all trajectories and timesteps.
  Update the policy, using a policy gradient estimate $\hat{g}$,
    which is a sum of terms $\nabla_\theta \log \pi(a_t|s_t, \theta)\hat{A}_t$.
    (Plug $\hat{g}$ into SGD or ADAM)
endfor

Practical Implementation with Autodiff

- Usual formula $\sum_t \nabla_\theta \log \pi(a_t|s_t;\theta)\hat{A}_t$ is inifficient–want to batch data
- Define "surrogate" function using data from current batch

$$L(\theta) = \sum_t \log \pi(a_t|s_t;\theta)\hat{A}_t$$

- Then policy gradient estimator $\hat{g} = \nabla_\theta L(\theta)$
- Can also include value function fit error

$$L(\theta) = \sum_t \left(\log \pi(z_t|s_t;\theta)\hat{A}_t - ||V(s_t) - \hat{R}_t||^2 \right)$$

Other choices for baseline?

Initialize policy parameter θ, baseline b

for iteration$=1, 2, \cdots$ **do**

Collect a set of trajectories by executing the current policy

At each timestep in each trajectory, compute

the *return* $R_t^{(s_t)} = \sum_{t'=t}^{T-1} r_{t'}$, and

the *advantage estimate* $\hat{A}_t = R_t - b(s_t)$.

$\tilde{Q}^{\pi}(s_t, a_t)$

Re-fit the baseline, by minimizing $||b(s_t) - R_t||^2$,

summed over all trajectories and timesteps.

Update the policy, using a policy gradient estimate $\hat{g}$,

which is a sum of terms $\nabla_\theta \log \pi(a_t|s_t, \theta)\hat{A}_t$.

(Plug $\hat{g}$ into SGD or ADAM)

endfor

Choosing the Baseline: Value Functions

- Recall Q-function / state-action-value function:

$$Q^{\pi,\gamma}(s,a) = \mathbb{E}_\pi \left[r_0 + \gamma r_1 + \gamma^2 r_2 \cdots | s_0 = s, a_0 = a \right]$$

- State-value function can serve as a great baseline

$$\begin{aligned} V^{\pi,\gamma}(s) &= \mathbb{E}_\pi \left[r_0 + \gamma r_1 + \gamma^2 r_2 \cdots | s_0 = s \right] \\ &= \mathbb{E}_{a\sim\pi}[Q^{\pi,\gamma}(s,a)] \end{aligned}$$

- Advantage function: Combining Q with baseline V

$$A^{\pi,\gamma}(s,a) = \underbrace{Q^{\pi,\gamma}(s,a)}_{} - \underbrace{V^{\pi,\gamma}(s)}_{}$$

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Likelihood Ratio / Score Function Policy Gradient

- Recall last time:

$$\nabla_\theta V(\theta) \quad \approx \quad (1/m) \sum_{i=1}^{m} R(\tau^{(i)}) \sum_{t=0}^{T-1} \nabla_\theta \log \pi_\theta(a_t^{(i)}|s_t^{(i)})$$

- Unbiased estimate of gradient but very noisy
- Fixes that can make it practical
  - Temporal structure (discussed last time)
  - Baseline
  - **Alternatives to using Monte Carlo returns $R * \tau^{(i)}$ as targets**

Choosing the Target

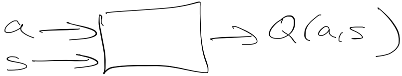
$MC = \sum_{t=1}^{T} r_t$

bootstrap TD / DP $\quad V(s_t) = r_t + \gamma \underbrace{V(s_{t+1})}_{\text{bootstrap}}$

- $R(\tau^{(i)})$ is an estimation of the value function from a single roll out
- Unbiased but high variance
- red~~blue~~uce variance by introducing bias using bootstrapping and function approximation (just like in we saw for TD vs MC, and in the value function approximation lectures)
- Estimate of V/Q is done by a **critic**
- **Actor-critic** methods maintain an explicit representation of both the policy and the value function, and update both
- A3C is very popular an actor-critic method

Why have two?
- approx errors diff
- stochastic π

cont actions



$\arg\max_a Q(a,s) \quad a$ cont.

Policy Gradient Formulas with Value Functions

target $V/Q(s_t, a_t)$

- Recall:

$$\nabla_\theta \mathbb{E}_\tau[R] = \mathbb{E}_\tau \left[\sum_{t=0}^{T-1} \nabla_\theta \log \pi(a_t|s_t, \theta) \left(\underbrace{\sum_{t'=t}^{T-1} r_{t'}} - b(s_t) \right) \right]$$

$$\nabla_\theta \mathbb{E}_\tau[R] \approx \mathbb{E}_\tau \left[\sum_{t=0}^{T-1} \nabla_\theta \log \pi(a_t|s_t, \theta) \left(\underline{Q(s_t, \mathbf{w})} - b(s_t) \right) \right]$$

- Letting the baseline be an estimate of the value V, we can represent the gradient in terms of the state-action advantage function

$$\nabla_\theta \mathbb{E}_\tau[R] = \mathbb{E}_\tau \left[\sum_{t=0}^{T-1} \nabla_\theta \log \pi(a_t|s_t, \theta) \hat{A}^\pi \underbrace{(s_t, a_t)} \right]$$

Choosing the Target: N-step estimators

$$\nabla_\theta V(\theta) \approx (1/m) \overbrace{\sum_{i=1}^{m} R(\tau^{(i)})}^{\text{MC estim}} \sum_{t=0}^{T-1} \nabla_\theta \log \pi_\theta(a_t^{(i)} | s_t^{(i)})$$

policy eval

Note that critic can select any blend between TD and MC estimators for the target to substitute for the true state-action value function.

$$\hat{R}_t^{(1)} = r_t + \gamma V(s_{t+1}) \qquad \text{TD}$$

k=20

$$\hat{R}_t^{(2)} = r_t + \gamma r_{t+1} + \gamma^2 V(s_{t+2}) \qquad \cdots$$

$$\hat{R}_t^{(\text{inf})} = r_t + \gamma r_{t+1} + \gamma^2 r_{t+1} + \cdots \qquad \text{MC}$$

If subtract baselines from the above, get advantage estimators

$$\hat{A}_t^{(1)} = r_t + \gamma V(s_{t+1}) - V(s_t)$$

$$\hat{A}_t^{(\text{inf})} = r_t + \gamma r_{t+1} + \gamma^2 r_{t+1} + \cdots - V(s_t)$$

$\hat{A}_t^{(1)}$ has low variance & high bias. $\hat{A}_t^{(\infty)}$ high variance but low bias.

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Updating the Policy Parameters Given the Gradient

Initialize policy parameter θ, baseline b

for iteration$=1, 2, \cdots$ **do**

  Collect a set of trajectories by executing the current policy

  At each timestep in each trajectory, compute

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    which is a sum of terms $\nabla_\theta \log \pi(a_t|s_t, \theta)\hat{A}_t$.

    (Plug $\hat{g}$ into SGD or ADAM)

endfor

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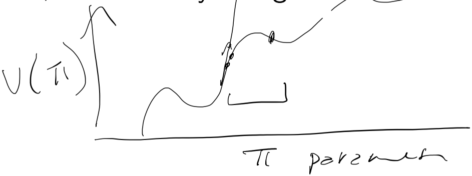
Policy Gradient and Step Sizes

(think policy improv)

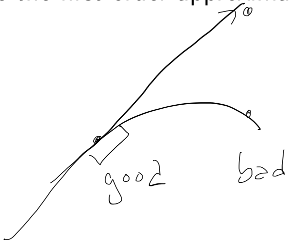
- Goal: Each step of policy gradient yields an updated policy π' whose value is greater than or equal to the prior policy π: $V^{\pi'} \geq V^{\pi}$
- Gradient descent approaches update the weights a small step in direction of gradient
- **First order** / linear approximation of the value function's dependence on the policy parameterization
- Locally a good approximation, further away less good



Why are step sizes a big deal in RL?

- Step size is important in any problem involving finding the optima of a function
- Supervised learning: Step too far $\rightarrow$ next updates will fix it
- Reinforcement learning
  - Step too far $\rightarrow$ bad policy
  - Next batch: collected under bad policy
  - **Policy is determining data collect!** Essentially controlling exploration and exploitation trade off due to particular poilcy parameters and the stochasticity of the policy
  - May not be able to recover from a bad choice, collapse in performance!

- Simple step-sizing: Line search in direction of gradient
  - Simple but expensive (perform evaluations along the line)
  - Naive: ignores where the first order approximation is good or bad



Policy Gradient Methods with Auto-Step-Size Selection

- Can we automatically ensure the updated policy π' whose value is greater than or equal to the prior policy π: $V^{\pi'} \geq V^{\pi}$?
- Consider this for the policy gradient setting, and hope to address this by modifying step size

Objective Function

- Goal: find policy parameters that maximize value function[35]

$$V(\theta) = \mathbb{E}_{\pi_\theta}\left[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t); \pi_\theta\right] \tag{1}$$

- where $s_0 \sim \mu(s_0)$, $a_t \sim \pi(a_t|s_t), s_{t+1} \sim P(s_{t+1}|s_t, a_t)$
- Have access to samples from the current policy π (param. by θ)
- Want to predict the value of a different policy (off policy learning!)

[35] For today we will primarily consider discounted value functions

Objective Function

- Goal: find policy parameters that maximize value function[37]

$$V(\theta) = \mathbb{E}_{\pi_\theta}\left[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t); \pi_\theta\right] \quad (2)$$

- where $s_0 \sim \mu(s_0)$, $a_t \sim \pi(a_t|s_t)$, $s_{t+1} \sim P(s_{t+1}|s_t, a_t)$
- Express expected return of another policy in terms of the advantage over the original policy (off policy learning)

new new old

$$V(\tilde{\theta}) = V(\theta) + \mathbb{E}_{\pi_{\tilde{\theta}}}\left[\sum_{t=0}^{\infty} \gamma^t A_\pi(s_t, a_t)\right] = V(\theta) + \sum_s \rho_{\tilde{\pi}}(s) \sum_a \tilde{\pi}(a|s) A_\pi(s, a)$$

$\int_a$

- where $\rho_{\tilde{\pi}}(s)$ is defined as the discounted weighted frequency of state s under policy $\tilde{\pi}$ (similar to in Imitation Learning lecture)
- We know the advantage A_π and $\tilde{\pi}$
- But we can't compute the above because we don't know $\rho_{\tilde{\pi}}$, the state distribution under the new proposed policy

[37] For today we will primarily consider discounted value functions

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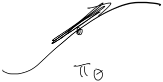
Local approximation

- Can we remove the dependency on the discounted visitation frequencies under the new policy?
- Substitute in the discounted visitation frequencies under the current policy to define a new objective function:

$V^{\tilde{\pi}}$

$$L_\pi(\tilde{\pi}) = V(\theta) + \sum_s \underbrace{\rho_\pi(s)}_{\text{support new policy}} \sum_a \tilde{\pi}(a|s) A_\pi(s,a) \tag{4}$$

- Note that $L_{\pi_{\theta_0}}(\pi_{\theta_0}) = V(\theta_0)$
- Gradient of L is identical to gradient of value function at policy parameterized evaluated at θ_0: $\nabla_\theta L_{\pi_{\theta_0}}(\pi_\theta)|_{\theta=\theta_0} = \nabla_\theta V(\theta)|_{\theta=\theta_0}$



Conservative Policy Iteration

- Is there a bound on the performance of a new policy obtained by optimizing the surrogate objective?
- Consider mixture policies that blend between an old policy and a different policy

dagger

$$\pi_{new}(a|s) = \underset{\alpha = 0}{(1-\alpha)}\pi_{old}(a|s) + \alpha\pi'(a|s) \tag{5}$$

- In this case can guarantee a lower bound on value of the new π_{new}:

$L_{\pi_{old}}(\pi_{old}) = V(\theta_{old}) + \sum_s \rho(\pi_{old}) \sum_a \pi_{old}(a|s) A_{\pi_{old}}(a,s)$

$L_{\pi_{old}}(\pi_{old}) = V(\theta_{old})$

$$\underline{V^{\pi_{new}}} \geq \underbrace{L_{\pi_{old}}(\pi_{new})}_{V(\theta_{old})} - \underbrace{\frac{2\epsilon\gamma}{(1-\gamma)^2}\alpha^2} \tag{6}$$

- where $\epsilon = \max_s \left|\mathbb{E}_{a\sim\pi'(a|s)}\left[A_\pi(s,a)\right]\right|$
- Check your understanding: is this bound tight if $\pi_{new} = \pi_{old}$? Can we remove the dependency on the discounted visitation frequencies under the new policy?

Find the Lower-Bound in General Stochastic Policies

- Would like to similarly obtain a lower bound on the potential performance for general stochastic policies (not just mixture policies)
- Recall $L_{\pi}(\tilde{\pi}) = V(\theta) + \sum_s \rho_\pi(s) \sum_a \tilde{\pi}(a|s) A_\pi(s,a)$

Theorem

Let $D_{TV}^{\max}(\pi_1, \pi_2) = \max_s D_{TV}(\pi_1(\cdot|s), \pi_2(\cdot|s))$. *Then*

$$V^{\pi_{new}} \geq \underline{L_{\pi_{old}}(\pi_{new})} - \frac{4\epsilon\gamma}{(1-\gamma)^2}\underline{(D_{TV}^{\max}(\pi_1, \pi_2))^2}$$

where $\epsilon = \max_{s,a} |A_\pi(s,a)|$.

- Note that $D_{TV}(p,q)^2 \leq D_{KL}(p,q)$ for prob. distrib p and q.
- Then the above theorem immediately implies that

$$\left[V^{\pi_{new}} \geq \underline{L_{\pi_{old}}(\pi_{new})} - \frac{4\epsilon\gamma}{(1-\gamma)^2} D_{KL}^{\max}(\pi_{old}, \pi_{new}) \right] \geq V^{\pi_{old}}$$

- where $D_{KL}^{\max}(\pi_1, \pi_2) = \max_s D_{KL}(\pi_1(\cdot|s), \pi_2(\cdot|s))$

Guaranteed Improvement[43]

- Goal is to compute a policy that maximizes the objective function defining the lower bound:

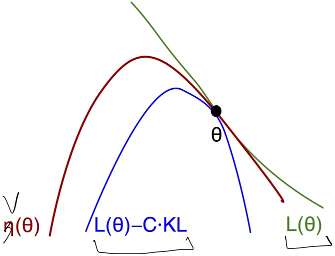
$$
\begin{aligned}
M_i(\pi) &= L_{\pi_i}(\pi) - \frac{4\epsilon\gamma}{(1-\gamma)^2} D_{KL}^{\max}(\pi_i, \pi) && (7) \\
V^{\pi_{i+1}} &\geq L_{\pi_i}(\pi) - \frac{4\epsilon\gamma}{(1-\gamma)^2} D_{KL}^{\max}(\pi_i, \pi) = M_i(\pi_{i+1}) && (8) \\
V^{\pi_i} &= M_i(\pi_i) && (9) \\
V^{\pi_{i+1}} - V^{\pi_i} &\geq M_i(\pi_{i+1}) - M_i(\pi_i) && (10)
\end{aligned}
$$

- So as long as the new policy π_{i+1} is equal or an improvement compab~~lue~~ to the old policy π_i with respect to the lower bound, we are guaranteed to to monotonically improve!
- The above is a type of Minorization-maximization (MM) algorithm

[43] $L_\pi(\tilde{\pi}) = V(\theta) + \sum_s \rho_\pi(s) \sum_a \tilde{\pi}(a|s) A_\pi(s,a)$

Guaranteed Improvement[45]

$$V^{\pi_{new}} \geq L_{\pi_{old}}(\pi_{new}) - \frac{4\epsilon\gamma}{(1-\gamma)^2} D_{KL}^{\max}(\pi_{old}, \pi_{new})$$



[45] $L_\pi(\tilde{\pi}) = V(\theta) + \sum_s \rho_\pi(s) \sum_a \tilde{\pi}(a|s) A_\pi(s, a)$

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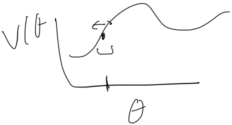
Optimization of Parameterized Policies[48]

- Goal is to optimize

$$\max_{\theta} L_{\theta_{old}}(\theta_{new}) - \frac{4\epsilon\gamma}{(1-\gamma)^2} D_{KL}^{\max}(\theta_{old}, \theta_{new}) = \underbrace{L_{\theta_{old}}(\theta_{new})} - \underbrace{C D_{KL}^{\max}(\theta_{old}, \theta_{new})}$$

- where C is the penalty coefficient
- In practice, if we used the penalty coefficient recommended by the theory above $C = \frac{4\epsilon\gamma}{(1-\gamma)^2}$, the step sizes would be very small
- New idea: Use a trust region constraint on step sizes. Do this by imposing a constraint on the KL divergence between the new and old policy.



$$\max_{\theta} L_{\theta_{old}}(\theta) \tag{11}$$

$$\text{subject to} D_{KL}^{s\sim\rho_{\theta_{old}}}(\theta_{old}, \theta) \leq \underline{\delta} \tag{12}$$

- This uses the average KL instead of the max (the max requires the KL is bounded at all states and yields an impractical number of constraints)

[48] $L_{\pi}(\tilde{\pi}) = V(\theta) + \sum_s \rho_{\pi}(s) \sum_a \tilde{\pi}(a|s) A_{\pi}(s, a)$

From Theory to Practice

- Prior objective:

$$\max_\theta L_{\theta_{old}}(\theta) \tag{13}$$

$$\text{subject to} D_{KL}^{s\sim\rho_{\theta_{old}}}(\theta_{old}, \theta) \leq \delta \tag{14}$$

where $L_\pi(\tilde{\pi}) = V(\theta) + \sum_s \rho_\pi(s) \sum_a \tilde{\pi}(a|s) A_\pi(s, a)$

- Don't know the visitation weights nor true advantage function
- Instead do the following substitutions:

$$\sum_s \rho_\pi(s) \rightarrow \frac{1}{1-\gamma} \mathbb{E}_{s\sim\rho_{\theta_{old}}}[\ldots], \quad \text{samples} \tag{15}$$

From Theory to Practice

- Next substitution:

$$\sum_a \pi_\theta(a|s_n) A_{\theta_{old}}(s_n, a) \rightarrow \mathbb{E}_{a \sim q}\left[\frac{\pi_\theta(a|s_n)}{q(a|s_n)} A_{\theta_{old}}(s_n, a)\right] \qquad (16)$$

- where q is some sampling distribution over the actions and s_n is a particular sampled state.
- This second substitution is to use importance sampling to estimate the desiblue sum, enabling the use of an alternate sampling distribution q (other than the new policy π_θ.)
- Third substitution:

$$A_{\theta_{old}} \rightarrow Q_{\theta_{old}} \qquad (17)$$

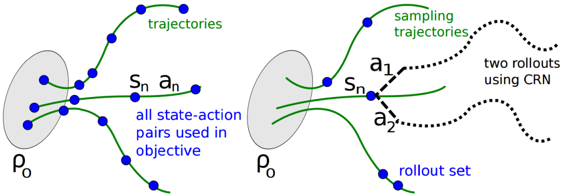
- Note that the above substitutions do not change solution to the above optimization problem

Selecting the Sampling Policy

- Optimize

$$\max_\theta \mathbb{E}_{s\sim\rho_{\theta_{old}}, a\sim q}\left[\frac{\pi_\theta(a|s)}{q(a|s)} Q_{\theta_{old}}(s,a)\right]$$
$$\text{subject to} \mathbb{E}_{s\sim\rho_{\theta_{old}}} D_{KL(}\pi_{\theta_{old}}(\cdot|s), \pi_\theta(\cdot|s)) \leq \delta$$

- Standard approach: sampling distribution is $q(a|s)$ is simply $\pi_{old}(a|s)$
- For the vine procedure see the paper



Searching for the Next Parameter

- Use a linear approximation to the objective function and a quadratic approximation to the constraint
- Constrained optimization problem
- Use conjugate gradient descent

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Practical Algorithm: TRPO

for iteration$=1, 2, \ldots$ **do**

  Run policy for T timesteps or N trajectories

  Estimate advantage function at all timesteps

  Compute policy gradient g

  Use CG (with Hessian-vector products) to compute $F^{-1}g$ where F is the Fisher information matrix

  Do line search on surrogate loss and KL constraint

end for

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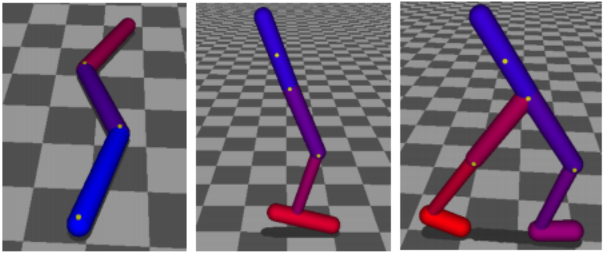
Practical Algorithm: TRPO

Applied to

- Locomotion controllers in 2D



- Atari games with pixel input

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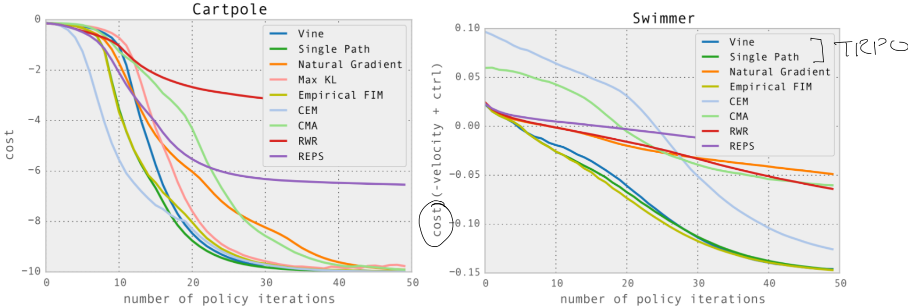
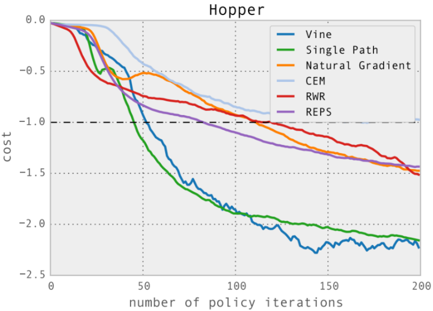
TRPO Results



TRPO Results



TRPO Summary

- Policy gradient approach
- Uses surrogate optimization function
- Automatically constrains the weight update to a trusted region, to approximate where the first order approximation is valid
- Empirically consistently does well
- Very influential: +350 citations since introduced a few years ago

Common Template of Policy Gradient Algorithms

for iteration$=1, 2, \ldots$ **do**
    Run policy for T timesteps or N trajectories
    At each timestep in each trajectory, compute target $Q^{\pi}(s_t, a_t)$, and baseline $b(s_t)$
policy eval
    Compute estimated policy gradient $\hat{g}$
    Update the policy using $\hat{g}$, potentially constrained to a local region
end for

Policy Gradient Summary

- Extremely popular and useful set of approaches
- Can input prior knowledge in the form of specifying policy parameterization
- You should be very familiar with REINFORCE and the policy gradient template on the prior slide
- Understand where different estimators can be slotted in (and implications for bias/variance)
- Don't have to be able to derive or remember the specific formulas in TRPO for approximating the objectives and constraints
- Will have the opportunity to practice with these ideas in homework 3