Advanced Topics in Reinforcement Learning

Lecture 17: Advanced Policy Gradient Methods

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Announcements

- Literature review due tonight @ 11:59pm
- Read “Between MDPs and Semi-MDPs:..” For next week
- Mid-course Survey
- Talk today at 2:30
- Upcoming dates:
  - Exam: November 6
  - SILO: Phil Thomas on Nov. 5

Learning Outcomes

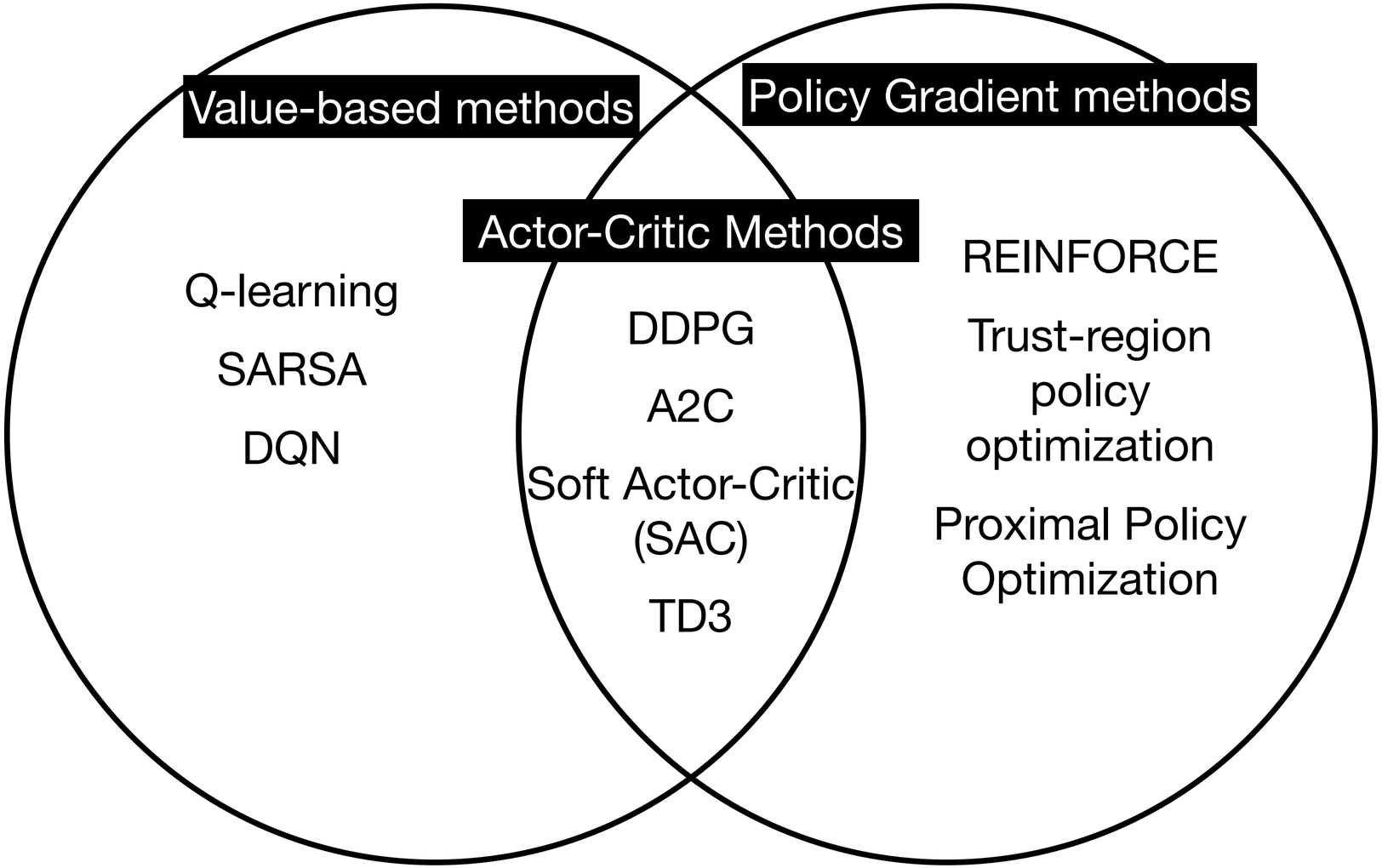
After this week, you will be able to:

1. Understand how to formulate the basic policy gradient RL approach.

2. Compare and contrast value-based, policy-based, and actor-critic model-free RL methods.

3. Identify key techniques in advanced policy-based RL methods.

Model-Free RL



Policy-based RL

- Policy gradient methods use a parameterized policy and learn policy parameters with gradient ascent.
- $\pi_\theta(a \mid s) = \Pr(A_t = a \mid S_t = s, \theta_t = \theta)$
- $J(\theta) = v_{\pi_\theta}(s_0)$
- $\theta_{t+1} \leftarrow \theta_t + \alpha \nabla_\theta \widehat{J(\theta_t)}$

$$\theta \rightarrow \pi_\theta(a \mid s) \rightarrow J(\theta)$$

Policy Parameterizations

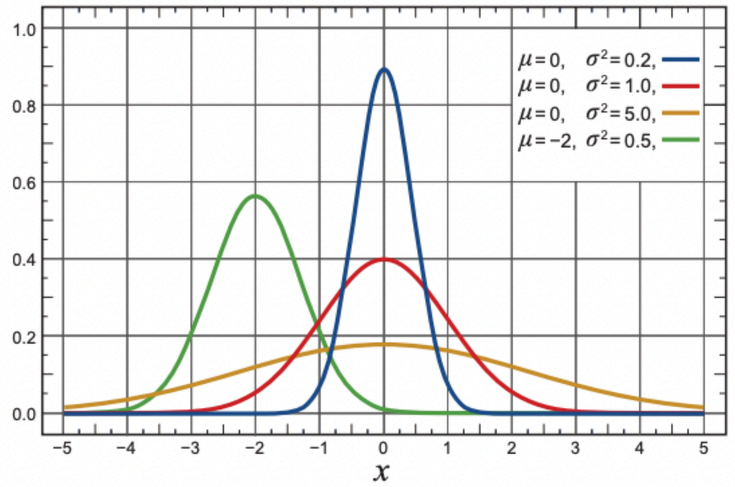
- Policy can be **any** parameterized and differentiable distribution.
- Need $\pi_\theta(A_t = a \,|\, s)$ and $\nabla_\theta \pi_\theta(A_t = a \,|\, s)$ exists.

Discrete Action Example

- $\Pr(A_t = a \,|\, S_t = s) \propto \exp(h(s, a, \theta))$
- $\nabla_\theta \ln \pi_\theta(a \,|\, s, \theta) = \nabla_\theta h(s, a, \theta) - \mathbf{E}_{\pi_\theta}[\nabla_\theta h(s, A, \theta)]$

Continuous Action Example

- $\Pr(A_t = a \,|\, S_t = s) = \mathcal{N}(\mu(s), \sigma(s))$
- $\mu(s) = f_\theta(s); \log \sigma(s) = f_\sigma(s)$
- $\nabla_\theta \ln \pi_\theta(a \,|\, s, \theta) = \frac{1}{\sigma(s)^2}(a - \mu(s)) \nabla_\theta f_\theta(s)$



Actor-Critic Methods

- REINFORCE uses a learned value function only to lower variance.
  - Monte Carlo return still drives which actions are reinforced. $\theta_{t+1} \leftarrow \theta_t + \alpha G_t \nabla \ln \pi_\theta(A_t \mid S_t)$
- Actor-critic methods use learned value functions to drive policy changes.
  - Actor: the policy.
  - Critic: value function.
- Can use state-value or action-value functions:
  - $\theta_{t+1} \leftarrow \theta_t + \alpha \delta_t \nabla_\theta \ln \pi(A_t \mid S_t)$
  - $\theta_{t+1} \leftarrow \theta_t + \alpha \hat{q}(S_t, A_t) \nabla_\theta \ln \pi(A_t \mid S_t)$

$$\delta_t \leftarrow R_{t+1} + \gamma \hat{v}(S_{t+1}, \mathbf{w}_t) - \hat{v}(S_t, \mathbf{w}_t)$$

$$\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t + \alpha \delta_t \nabla_{\mathbf{w}} \hat{v}(S_t, \mathbf{w})$$

Actor-Critic Methods

One-step Actor–Critic (episodic), for estimating $\pi_{\boldsymbol{\theta}} \approx \pi_*$

Input: a differentiable policy parameterization $\pi(a|s,\boldsymbol{\theta})$
Input: a differentiable state-value function parameterization $\hat{v}(s,\mathbf{w})$
Parameters: step sizes $\alpha^{\boldsymbol{\theta}} > 0$, $\alpha^{\mathbf{w}} > 0$
Initialize policy parameter $\boldsymbol{\theta} \in \mathbb{R}^{d'}$ and state-value weights $\mathbf{w} \in \mathbb{R}^{d}$ (e.g., to $\mathbf{0}$)
Loop forever (for each episode):
  Initialize S (first state of episode)
  $I \leftarrow 1$
  Loop while S is not terminal (for each time step):
    $A \sim \pi(\cdot|S,\boldsymbol{\theta})$
    Take action A, observe S', R
    $\delta \leftarrow R + \gamma \hat{v}(S',\mathbf{w}) - \hat{v}(S,\mathbf{w})$ (if S' is terminal, then $\hat{v}(S',\mathbf{w}) \doteq 0$)
    $\mathbf{w} \leftarrow \mathbf{w} + \alpha^{\mathbf{w}} \delta \nabla \hat{v}(S,\mathbf{w})$
    $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \alpha^{\boldsymbol{\theta}} I \delta \nabla \ln \pi(A|S,\boldsymbol{\theta})$
    ~~$I \leftarrow \gamma I$~~
    $S \leftarrow S'$

Is the policy gradient a gradient? Nota and Thomas. 2020.

Patrick’s Presentation

- Soft Actor Critic
- Haarnoja et al. 2018
- Slides

Deterministic Policy Gradients

- Actor-critic limitations: **Random sampling for both states and actions.**
  - Can still have high variance (like REINFORCE) and also introduce bias into gradient estimates.
  - On-policy or require importance sampling to be off-policy.
- Deterministic policy gradient methods overcome these limitations in continuous action problems:
  - Learn a deterministic policy $A_t \leftarrow \pi_\theta(S_t)$.
  - Approximate $q_\pi(s, a)$ with a function approximator, $\hat{q}$, that is differentiable w.r.t. the action.
  - $\nabla_\theta J(\theta) \propto \mathbf{E}[\nabla_a \hat{q}(S_t, A_t) \nabla_\theta \pi_\theta(a) \,|\, S_t \sim d_b, A_t \sim b]$

Can interpret as approximating Q-learning for continuous actions

Deterministic Policy Gradient Algorithms. Silver et al. 2014.

Deterministic Policy Gradients

- Basis for several state-of-the-art off-policy deep RL algorithms:
  - Deep Deterministic Policy Gradient (DDPG). Lilicrap et al. 2015.
  - Twin Delayed DDPG (TD3). Fujimoto et al. 2018.
    - Trains two critics and uses minimum like double Q-learning.
  - Soft Actor-Critic (SAC). Haarnoja et al. 2018.
    - Trains stochastic actor using reparameterization trick to lower variance; also double Q-learning technique.

Natural Policy Gradients

$$\theta \rightarrow \pi_\theta(a \mid s) \rightarrow J(\theta)$$

- $\nabla_\theta J(\theta)$ is the direction in which an infinitesimally small change **in** θ will increase $J(\theta)$ most.
  - "Small" is defined using the euclidean norm, $||\theta||_2^2$.
  - Makes step-size sensitive to how the policy is parameterized.
- The natural gradient, $\tilde{\nabla}_\theta J(\theta)$, is the direction in which an infinitesimally small change in π_θ will increase $J(\theta)$ most. **Parameterization no longer matters!**
- $\tilde{\nabla}_\theta J(\theta) = F^{-1} \nabla_\theta J(\theta)$ where F is the $d \times d$ Fisher information matrix.

A Natural Policy Gradient. Kakade. 2001

Natural gradient works efficiently in learning. Amari. 1998

d: policy parameter dimension

Trust Region Policy Optimization (TRPO)

- Two limitations of natural policy gradients:
  - Computational complexity of estimating Fisher Information matrix.
  - Still have to set a step-size parameter.
- Trust Region Policy Optimization (TRPO):
  - Approximately solves for the natural gradient (direction to change θ) with conjugate gradient algorithm.
  - Uses a line-search to find α that most increases surrogate objective $L(\theta')$ subject to the constraint $D_{KL}(\pi_\theta || \pi_{\theta'}) \leq \epsilon$.

Trust Region Policy Optimization. Schulman et al. 2015.

Yunhao’s Presentation

- Proximal Policy Optimization Algorithms
- Schulman et al. 2017.
- Slides

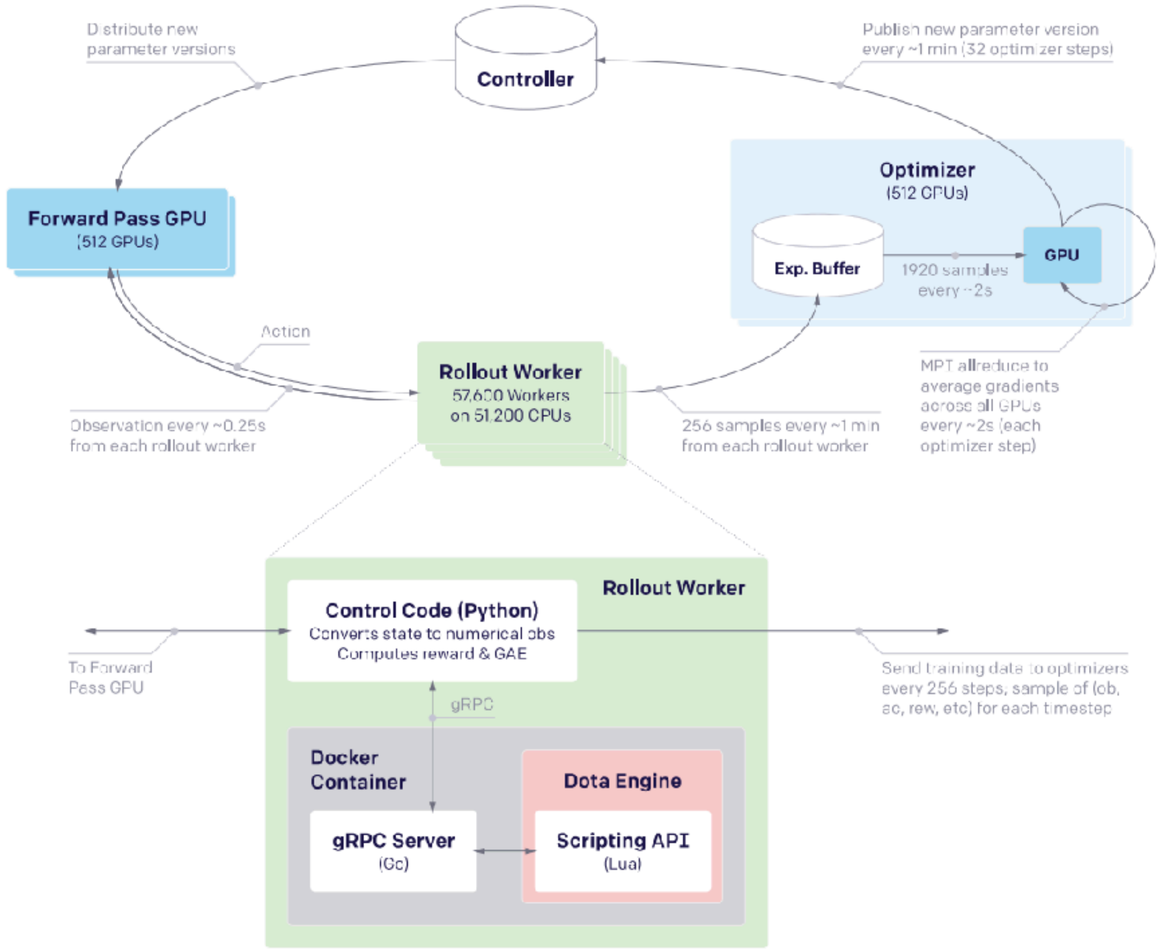
Proximal Policy Optimization (PPO)

- Large scale deep RL requires decoupling policy optimization from environment interaction; enables efficient use of GPUs and parallelized data collection.
  - Requires off-policy algorithms; TPRO is an on-policy algorithm
- PPO takes inspiration from TRPO but makes off-policy updates with SGD.
  - Optimize the objective $\mathbf{E}_{s,a\sim\pi_{\theta_k}}[L(s,a,\theta_k,\theta)]$ with SGD.

Optimize θ with (s,a,r,s') collected while running θ_k

  - $L(s,a,\theta_k,\theta) = \min(\frac{\pi_\theta(a\,|\,s)}{\pi_{\theta_k}(a\,|\,s)}A^{\pi_{\theta_k}}(s,a), \texttt{clip}(\frac{\pi_\theta(a\,|\,s)}{\pi_{\theta_k}(a\,|\,s)}, 1-\epsilon, 1+\epsilon)A^{\pi_{\theta_k}}(s,a))$
  - No guarantee that π_{θ_k} and $\pi_{\theta_{k+1}}$ won't be too different; implementations may use other techniques to mitigate this.

What can PPO do?



What can PPO do?

Comparing Methods

- PPO / TRPO:
  - Stable learning, learn well out of the box, comparatively low wall-clock time
  - Sample inefficient
- Soft actor-critic / TD3 / DDPG
  - Less stable learning, may require more tuning, more wall-clock time
  - Sample efficient

Summary

- Actor-critic methods use a learned value function as a replacement for the return in basic policy gradient methods.
- REINFORCE —> Natural policy gradients —> TRPO —> PPO
- In continuing RL problems, average reward can be a more suitable policy optimization objective
  - Algorithms developed for discounted return can still be used with *differential* value functions.

Action Items

- Complete literature review.
- Begin studying for midterm exam
- Read “Between MDPs and semi-MDPs:…”