Gradient Actor-Critic Algorithm under Off-policy Sampling and Function Approximation

Youngsuk Park

PhD Candidate, Stanford University

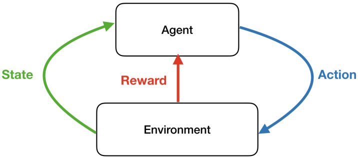
Dec 3, 2018

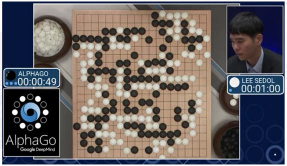
Outline

- RL introduction
- RL background
  - Class of RL algorithm
  - Modularity and scalablity of RL
- New actor-critic method: gradient actor-critic (GAC)
- Empirical studies
  - simple two-state examples
  - classic control problems
  - atari game and mojuco environment (next)

Introduction: Reinforcement Learning Framework

Consider the following interface





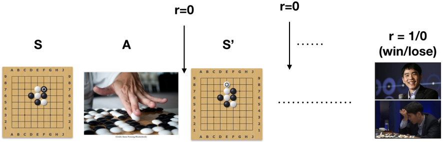
- agent's goal is to select actions to maximize long-term rewards
  - long-term rewards is called *value* V
  - learn policy π(state)=action, rule of how to act on state
- how can agent achieve the goal efficiently?
  - cannot store/refer to all past history, e.g.) $\#$state $= 10^{170}$ in Go
  - use RL that has the collection of algorithms to find optimal policy

Background: Value-based Method

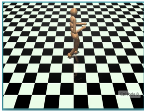
Q-learning is one of value-base methods

- predictor learns $Q(s,a)$ value, future rewards at state s for action a

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \max_{a} Q(s',a) - Q(s,a)]$$



  - control is determined by Q-value in prediction
  - pros: online learning, etc
  - cons: does not scale for continuous (high-dim discrete) actions space



Background: Policy Gradient Method

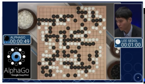
REINFORCE is one of policy gradient methods

- policy π is parameterized with θ, e.g.) $\pi(a \mid s; \theta) = \mathcal{N}(\theta^T \phi(s), 1)$
- learns policy parameter θ

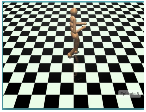
$$\theta \leftarrow \theta + \beta(\sum_{i=t}^{\infty} r_i - b)\nabla \ln \pi$$

where b is some baseline

- no prediction/estimation of any value w.r.t π
- cons: have to wait long time (off-line), etc

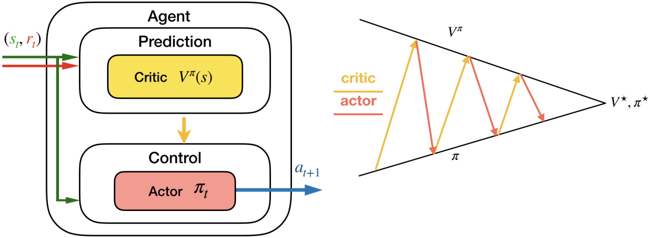


- pros: scales well for continuous action space, etc



Background: Actor-Critic Methods

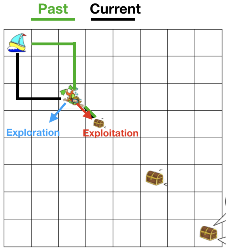
actor-critic methods is hybrid of value-based and policy gradient methods

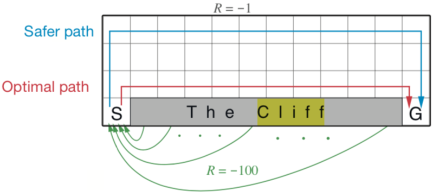


- critic (in prediction) learns to estimate V^π, giving feedback to actor
- actor (in control) improves policy π and generates actions
- overcomes weakness of previous two methods
  - scalable for continuous action space (vs. value-based)
  - online learning (vs. policy gradient)
- has two separate components

Background: Control with Exploration/Exploitation

- in control, exploration/exploitation can be important
  - just exploit via best policy learned so far (from history)
  - or maybe consider to explore more (for the better future)

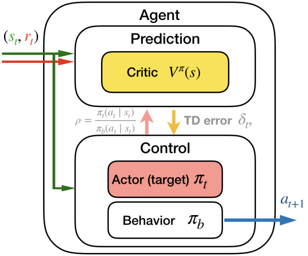




- Q) while exploring environment, can we still learn optimal policy?
  - yes, we can via off-policy learning!
  - behavior policy π_b just generates actions, target policy π_t is learned

Gradient Actor-Critic for Off-Policy

- [1]Off-PAC



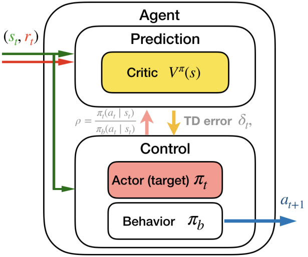
$$\text{(critic) } w \leftarrow w + \alpha\rho\delta\phi(s)$$
$$\text{(actor) } \theta \leftarrow \theta + \beta\rho\delta\nabla\ln\pi$$

- state feature $\phi(s)$, TD error $\delta = r(s,a) + \gamma w^T\phi(s') - w^T\phi(s)$
- ratio $\rho = \frac{\pi_t(a|s)}{\pi_b(a|s)}$

[1]Degris, T., White, M. and Sutton, R. S. (2012). Off-Policy Actor-Critic.

Gradient Actor-Critic for Off-Policy

- (new) gradient actor-critic (with parameter λ)



$$\text{(critic) } w \leftarrow w + \alpha \rho \delta e^\lambda$$

$$\text{(actor) } \theta \leftarrow \theta + \beta \rho \delta \psi^\lambda$$

- ratio $\rho = \frac{\pi_t(a|s)}{\pi_b(a|s)}$
- e^λ is the combination of $(\phi(s_t), \ldots, \phi(s_0))$
- ψ^λ is the combination of $\nabla \ln \pi(a_t \mid s_t), \ldots, \nabla \ln \pi(a_0 \mid s_0)$

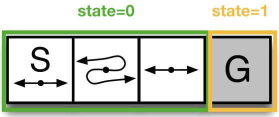
Properties of Gradient Actor-Critic

- GAC allows bootstrap parameter $\lambda \in [0, 1]$

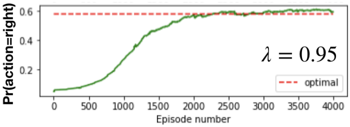
$$\text{(critic) } w \leftarrow w + \alpha \rho \delta e^{\lambda}$$
$$\text{(actor) } \theta \leftarrow \theta + \beta \rho \delta \psi^{\lambda}$$

  where λ decides how much remember/forget past features
- prove GAC converges to optimal for $\lambda = 1$
- show that Off-PAC can have bias (see in examples later)
- in practice, choose $\lambda = 1 - \epsilon$ for less variance but (potential) bias and
- prove its bias is within $O\left(\frac{\gamma}{(1-\gamma)^2}\epsilon\right)$

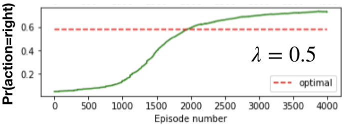
Examples 1: Short Corridor



- 4 corridors where 2nd corridor is abnormal
- agent can only distinguish goal or non-goal corridor
- optimal policy is stochastic with Pr(action=right)$= 0.6$



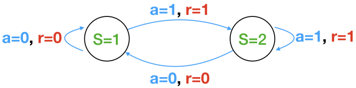
alpha=0.0005. beta=5e-05 gamma=0.95. Averaged over 1 trials



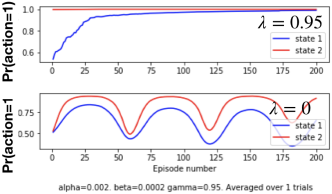
alpha=0.0005. beta=5e-05 gamma=0.95. Averaged over 1 trials

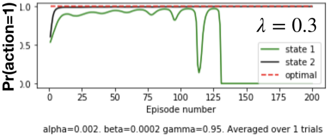
- behavior policy is uniform-random, still learn optimal with $\lambda \approx 1$
- large biased solution for $\lambda < 0.8$
- note Q-learning cannot learn optimal

Examples 2: θ to 2θ Counter example



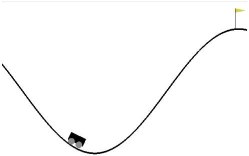
- two state $s = 1, 2$
- optimal policy is taking action 1 for every state
- use the feature $\phi(s=1) = 1$, $\phi(s=2) = 2$, thus $V_\theta(s) = s\theta$

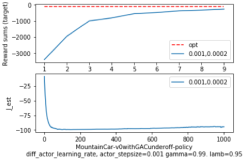




- with $\lambda \approx 1$, GAC learn optimal
- Off-PAC ($\lambda = 0$) fails

Examples 3: Mountain Car

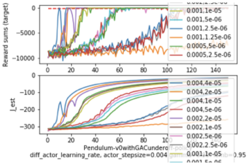




- *continuous* state space (position, velocity) in $\mathbf{R}^2$
- discrete action space [left, stay, right]
- car moves according to dynamical sytem
- reward is -1 if it has not reached the goal yet

- behavior policy is uniform random (timesteps to reach > 5000)
- every 100 episodes, evaluate the performance of target policy

Examples 4: Pendulum



- *continuous* state (angle, angular velocity), represented by tilecoding
- *continuous* action (torque), modeled by Gaussian
- reward is based on position and velocity
- goal is to make pendulum stand

Examples 5: Mojuco and Atri Game (Next)

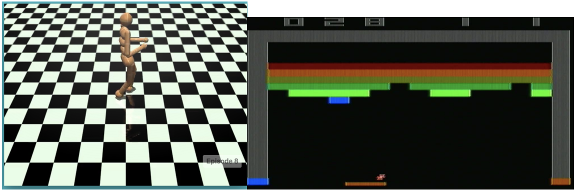


Figure: humanoid in Mojuco and atari game in Gym

- input is just pixel information
- need to use DL to represent state from input

Summary & Future Work

- RL agent has two components: prediction and control
- actor-critic is scalable on action and state space (under function approx.)
- off-policy (with target and behavior) can allow distributed learning
- GAC is (first) convergent actor-critic method under off-policy and function approximation
- we can warm-start with reasonable behavior
- next: apply GAC in mojuco and atari game environment that use DL to represent features