

September 28

1 Lecture: Policy Gradient

For simplicity, let us first consider a one-step decision-making process (also known as a contextual bandit).

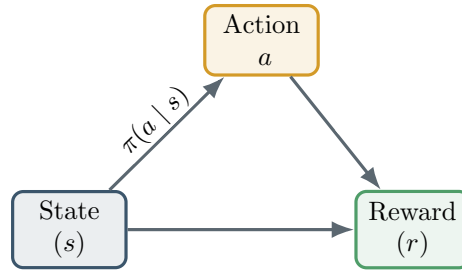
Problem Setup Let $s \in \mathcal{S}$ be the state vector of the environment, and let $a \in \mathcal{A}$ be the action taken by the agent. The reward function is denoted by $r(a, s)$. The agent's behavior is characterized by a policy, which is conveniently represented as a conditional probability distribution, $\pi(a | s)$, specifying the probability of selecting each action a given a state s . The objective is to find the optimal policy π^* that maximizes the expected reward:

$$R(\pi) = \mathbb{E}_{s \sim p_0} \mathbb{E}_{a \sim \pi(\cdot | s)} [r(a, s)] = \sum_{s, a} p_\pi(a, s) r(a, s),$$

where p_0 denotes the distribution of states, and we have $p_\pi(a, s)$ denotes the joint distribution of (a, s) when policy π is used:

$$p_\pi(a, s) = \pi(a | s) p_0(s).$$

Typically, p_0 is unknown to us, but observed through a collection of data $\{s^{(i)}\}$ drawn from p_0 .



Policy Gradient In practice, the policy $\pi(a | s) = \pi_\theta(a | s)$ is parameterized by a function with parameter θ . Assume the state-action space $\mathcal{S} \times \mathcal{A}$ is finite or countable, the gradient of the expected reward with respect to θ is

$$\begin{aligned} \nabla_\theta R(\pi_\theta) &= \nabla_\theta \left(\sum_{s, a} p_0(s) \pi_\theta(a | s) r(a, s) \right) \\ &= \sum_{s, a} p_0(s) \nabla_\theta \pi_\theta(a | s) r(a, s) \\ &= \sum_{s, a} p_0(s) \pi_\theta(a | s) \frac{\nabla_\theta \pi_\theta(a | s)}{\pi_\theta(a | s)} r(a, s) \\ &= \mathbb{E}_{p_{\pi_\theta}} [r(a, s) \nabla_\theta \log \pi_\theta(a | s)], \end{aligned}$$

where the parts depending on θ are highlighted, and we use the log-derivative trick $\nabla_\theta \log \pi = \nabla_\theta \pi_\theta / \pi_\theta$. This allows us to express the derivative of an expectation with respect to a distribution as the expectation of the reward weighted by $\nabla_\theta \log \pi_\theta(a | s)$.

Reward Baseline For any policy π^θ , it is easy to prove the following identity:

$$\mathbb{E}_{a \sim \pi_\theta(\cdot|s)}[\nabla_\theta \log \pi_\theta(a|s)] = 0, \quad \forall s, \theta.$$

Hence, we can generalize the gradient formula above to

$$\nabla_\theta R(\pi_\theta) = \mathbb{E}_{p_{\pi_\theta}} [(r(a, s) - v(s)) \nabla_\theta \log \pi_\theta(a|s)], \quad (1)$$

where $v(s)$ is *any* function that does not depend on the action a . The choice of v does not alter the expectation of the formula, but a proper choice of v can reduce the variance of the mean estimation given empirical observations.

One common choice of baseline is $v(s) = \mathbb{E}_{a \sim \pi_\theta(\cdot|s)}[r(a, s)]$, in which case the difference $r(a, s) - v(s)$ is known as the *advantage function*:

$$A(a, s) = r(a, s) - v(s).$$

A positive value $A(a, s) > 0$ (respectively, negative < 0) indicates that the action a performs above (respectively, below) the average.

On-Policy Estimation In practice, given observations $\{s^{(i)}\}$ drawn from p_0 and $a^{(i)} \sim \pi^\theta(\cdot|s^{(i)})$ drawn from the ongoing policy π^θ , the gradient can be estimated by

$$\nabla_\theta R(\pi_\theta) \approx \frac{1}{n} \sum_{i=1}^n A^{(i)} \nabla_\theta \log \pi_\theta(a^{(i)} | s^{(i)}), \quad A^{(i)} = A(a^{(i)}, s^{(i)}). \quad (2)$$

The gradient ascent update, also known as REINFORCE,

$$\theta \leftarrow \theta + \epsilon \nabla_\theta R(\pi_\theta).$$

Intuitively, the gradient $\nabla_\theta \log \pi_\theta(a^{(i)} | s^{(i)})$ for data points $(a^{(i)}, s^{(i)})$ with positive advantages $A^{(i)} > 0$ is positively weighted, increasing the probability $\pi_\theta(a | s)$ during gradient ascent. Conversely, for data points with negative advantages, the gradient is negatively weighted, decreasing the probability.

Connection to Weighted MLE Assuming the data $\{a^{(i)}, s^{(i)}\}$ are fixed, the policy gradient $\nabla_\theta R(\pi_\theta)$ coincides with the gradient of the $A^{(i)}$ -weighted log-likelihood function:

$$\ell(\pi_\theta) = \frac{1}{n} \sum_{i=1}^n A^{(i)} \log \pi_\theta(a^{(i)} | s^{(i)}).$$

This aligns with the intuition of maximizing $\log \pi(a | s)$ for data points with large (and positive) $A^{(i)}$, while minimizing the log-likelihood for negative $A^{(i)}$.

The key difference, however, is that the data $\{a^{(i)}, s^{(i)}\}$ are drawn from the policy π_θ and thus depend on the current parameter θ . As θ is updated during policy optimization, the data must either be regenerated or reweighted to reflect changes in π_θ . In contrast, maximum likelihood estimation assumes the data are fixed.

Hence, policy optimization can be viewed as an adaptively weighted maximum likelihood estimation (MLE), where the weights ($A^{(i)}$) are adjusted across iterations using newly generated data.

Off-Policy Estimation via Importance Sampling The gradient estimation in (2) is *on-policy*, because the actions a must be drawn from the current policy $\pi_\theta(\cdot|s)$. This does not yield efficient use of data as new actions must be rolled out once the policy is updated, and data from different policies cannot be used. In comparison, *off-policy* methods allow us to leverage actions from different policies.

One common approach to off-policy estimation is importance sampling. Assume that the data $\{a^{(i)}, s^{(i)}\}$ are drawn from a *behavior policy* π^{data} . Using importance sampling, we have

$$\begin{aligned}\nabla_\theta R(\pi_\theta) &= \mathbb{E}_{p_{\pi^{\text{data}}}} \left[\frac{\pi_\theta(a|s)}{\pi^{\text{data}}(a|s)} A(a, s) \nabla_\theta \log \pi_\theta(a | s) \right] \\ &\approx \frac{1}{z} \sum_{i=1}^n w^{(i)} A^{(i)} \nabla_\theta \log \pi_\theta(a^{(i)} | s^{(i)}),\end{aligned}$$

where $w^{(i)}$ is the importance weight:

$$w^{(i)} = \frac{\pi_\theta(a^{(i)}|s^{(i)})}{\pi^{\text{data}}(a^{(i)}|s^{(i)})},$$

and the normalization constant z is often taken as $z = \sum_i w^{(i)}$.

Remark 1. In RL, *on-policy methods* update the policy using data collected from the current policy itself. *Off-policy methods* learn from data collected under a different policy, allowing reuse of past experiences and improving sample efficiency, but at the cost of a distribution mismatch between the behavior policy π^{data} and the target policy π_θ . *Offline RL* is the case of off-policy learning where training relies entirely on a fixed dataset with no further interaction.

References