CS294-112 Deep Reinforcement Learning HW2: Policy Gradients

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Problem 1. State-dependent baseline:

$$\sum_{t=1}^{T} \mathbb{E}_{\tau \sim p_{\theta}(\tau)} \left[\nabla_{\theta} \log \pi_{\theta}(a_t | s_t) \left(b(s_t) \right) \right] = 0.$$
 (1)

(a) Please show equation 1 by using the law of iterated expectations, breaking $\mathbb{E}_{\tau \sim p_{\theta}(\tau)}$ by decoupling the state-action marginal from the rest of the trajectory.

Given
$$p_{\theta}(\tau) = p_{\theta}(s_t, a_t) p_{\theta}(\tau/s_t, a_t | s_t, a_t)$$
, we write:

$$\begin{split} &\sum_{t=1}^{T} \mathbb{E}_{\tau \sim p_{\theta}(\tau)} \left[\nabla_{\theta} \log \pi_{\theta}(a_{t}|s_{t}) \left(b(s_{t})\right) \right] \\ &= \sum_{t=1}^{T} \mathbb{E}_{p_{\theta}(s_{t},a_{t})} \left[\mathbb{E}_{p_{\theta}(\tau/s_{t},a_{t}|s_{t},a_{t})} \left[\nabla_{\theta} \log \pi_{\theta}(a_{t}|s_{t}) \left(b(s_{t})\right) \right] \right] \\ &= \sum_{t=1}^{T} \int_{s_{t}} p_{\theta}(s_{t},a_{t}) \int_{a_{t}} p_{\theta}(a_{t}|s_{t}) \nabla_{\theta} \log \pi_{\theta}(a_{t}|s_{t}) \left(b(s_{t})\right) da_{t} ds_{t} \\ & \text{(since } p_{\theta}(\tau/s_{t},a_{t}|s_{t},a_{t}) = p_{\theta}(a_{t}|s_{t}) \right) \\ &= \sum_{t=1}^{T} \int_{s_{t}} p_{\theta}(s_{t},a_{t}) \int_{a_{t}} \nabla_{\theta} \pi_{\theta}(a_{t}|s_{t}) \left(b(s_{t})\right) da_{t} ds_{t} \\ & \text{(since } p_{\theta}(a_{t}|s_{t}) \nabla_{\theta} \log \pi_{\theta}(a_{t}|s_{t}) = \nabla_{\theta} \pi_{\theta}(a_{t}|s_{t}), \, p_{\theta} \text{ and } \pi_{\theta} \text{ are the same)} \\ &= \sum_{t=1}^{T} \int_{s_{t}} p_{\theta}(s_{t},a_{t}) b(s_{t}) \nabla_{\theta} \int_{a_{t}} \pi_{\theta}(a_{t}|s_{t}) da_{t} ds_{t} \\ &= \sum_{t=1}^{T} \int_{s_{t}} p_{\theta}(s_{t},a_{t}) b(s_{t}) \nabla_{\theta} 1 da_{t} ds_{t} = 0 \\ &\text{(since } \int_{a_{t}} \pi_{\theta}(a_{t}|s_{t}) da_{t} = 1, \nabla_{\theta} 1 = 0) \end{split}$$

- (b) Alternatively, we can consider the structure of the MDP and express $p_{\theta}(\tau)$ as a product of the trajectory distribution up to s_t (which we denote as $(s_{1:t}, a_{1:t-1})$) and the trajectory distribution after s_t conditioned on the first part (which we denote as $(s_{t+1:T}, a_{t:T}|s_{1:t}, a_{1:t-1})$):
 - (a) Explain why, for the inner expectation, conditioning on $(s_1, a_1, ..., a_{t^*-1}, s_{t^*})$ is equivalent to conditioning only on s_{t^*} .

Since the Markov chain is memoryless, the current state/action only depends on its most recent action/state.

(b) Please show equation 1 by using the law of iterated expectations, breaking $\mathbb{E}_{\tau \sim p_{\theta}(\tau)}$ by decoupling trajectory up to s_t from the trajectory after s_t .

Given

$$p_{\theta}(\tau) = p_{\theta}(s_{1:t}, a_{1:t-1}) p_{\theta}(s_{t+1:T}, a_{t:T} | s_{1:t}, a_{1:t-1})$$
$$= p_{\theta}(s_{1:t}, a_{1:t-1}) p_{\theta}(s_{t+1:T}, a_{t:T} | s_{t})$$

We write:

$$\begin{split} &\sum_{t=1}^{T} \mathbb{E}_{\tau \sim p_{\theta}(\tau)} \left[\nabla_{\theta} \log \pi_{\theta}(a_{t}|s_{t}) \left(b(s_{t}) \right) \right] \\ &= \mathbb{E}_{p_{\theta}(s_{1:t^{*}}, a_{1:t^{*}-1})} \left[\mathbb{E}_{p_{\theta}(s_{t^{*}+1:T}, a_{t^{*}:T}|s_{t^{*}})} \left[\sum_{t=1}^{T} \nabla_{\theta} \log \pi_{\theta}(a_{t}|s_{t}) \left(b(s_{t}) \right) \right] \right] \\ &= \mathbb{E}_{p_{\theta}(s_{1:t^{*}}, a_{1:t^{*}-1})} \left[\mathbb{E}_{p_{\theta}(s_{t^{*}+1:T}, a_{t^{*}:T}|s_{t^{*}})} \left[\sum_{t=t^{*}}^{T} \nabla_{\theta} \log \pi_{\theta}(a_{t}|s_{t}) \left(b(s_{t}) \right) \right] \right] \\ &\qquad \qquad \left(\text{truncating the head of sum because probability distribution is } p_{\theta}(s_{t^{*}+1:T}, a_{t^{*}:T}|s_{t^{*}}) \right) \end{split}$$

$$\begin{split} &= \mathbb{E}_{p_{\theta}(s_{1:t^*}, a_{1:t^*-1})} \left[\mathbb{E}_{p_{\theta}(s_{t^*+1:T}, a_{t^*:T} | s_{t^*})} \left[\nabla_{\theta} \log \prod_{t=t^*}^T \pi_{\theta}(a_t | s_t) \left(b(s_t) \right) \right] \right] \\ &= \mathbb{E}_{p_{\theta}(s_{1:t^*}, a_{1:t^*-1})} \left[\mathbb{E}_{p_{\theta}(s_{t^*+1:T}, a_{t^*:T} | s_{t^*})} \left[\nabla_{\theta} \log \pi_{\theta}(s_{t^*+1:T}, a_{t^*:T} | s_t) \left(b(s_{t^*}) \right) \right] \right] \\ &= \int_{s_t} p_{\theta}(s_{1:t^*}, a_{1:t^*-1}) \int_{a_t} p_{\theta}(s_{t^*+1:T}, a_{t^*:T} | s_{t^*}) \nabla_{\theta} \log \pi_{\theta}(s_{t^*+1:T}, a_{t^*:T} | s_t) \left(b(s_t) \right) da_t ds_t \\ &= \int_{s_t} p_{\theta}(s_{1:t^*}, a_{1:t^*-1}) \int_{a_t} \nabla_{\theta} \pi_{\theta}(s_{t^*+1:T}, a_{t^*:T} | s_t) \left(b(s_{t^*}) \right) da_t ds_t \\ &= \int_{s_t} p_{\theta}(s_{1:t^*}, a_{1:t^*-1}) b(s_{t^*}) \nabla_{\theta} \int_{a_t} \pi_{\theta}(s_{t^*+1:T}, a_{t^*:T} | s_t) da_t ds_t \\ &= \int_{s_t} p_{\theta}(s_{1:t^*}, a_{1:t^*-1}) b(s_{t^*}) \nabla_{\theta} 1 da_t ds_t = 0 \\ &\qquad \qquad \text{(since } \int_{a_t} \pi_{\theta}(s_{t^*+1:T}, a_{t^*:T} | s_t) da_t = 1, \nabla_{\theta} 1 = 0) \end{split}$$