note

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1 Markov Decision Process

$$r_{t_0}^{\gamma} = \sum_{t=t_0}^{\infty} \gamma^{t-t_0} r(s_t, a_t)$$
$$J(\pi) = \mathbb{E}[r_0^{\gamma}; \pi]$$

$$J(\pi) = \mathbb{E}_{s \sim \rho^{\pi}(\cdot), \ a \sim \pi(\cdot|s)}[r(s, a)]$$

Optimization Problem:

$$\max_{\pi} J(\pi)$$

$$V^{\pi}(s) = \mathbb{E}[r_t^{\gamma}|S_t = s; \pi]$$
$$Q^{\pi}(s, a) = \mathbb{E}[r_t^{\gamma}|S_t = s, A_t = a; \pi]$$

2 Value Function

$$V^{\pi}(s) = \mathbb{E}_{a \sim \pi(\cdot|s)}[Q^{\pi}(s, a)]$$
$$Q^{\pi}(s, a) = r(s, a) + \mathbb{E}_{s' \sim p(\cdot|s, a)}[V^{\pi}(s')]$$

$$V(s) = V^*(s) = \max_{\pi} V^{\pi}(s)$$

$$Q(s, a) = Q^*(s, a) = \max_{\pi} Q^{\pi}(s, a)$$

$$V(s) = \max_{a} Q^{\pi}(s, a)$$

Value Function Something

$$Q(s, a) = r(s, a) + \mathbb{E}_{s' \sim p(\cdot | s, a)}[V(s')]$$

= $r(s, a) + \mathbb{E}_{s' \sim p(\cdot | s, a)}[\max_{a'} Q(s', a')]$

Proof. Before

$$Q(s, a) = \max_{\pi} Q^{\pi}(s, a)$$
$$= r(s, a) + \max_{\pi} \mathbb{E}_{s' \sim p(\cdot|s, a)}[V(s')]$$

After.

(Definition) Advantage Function Something

$$A^{\pi}(s, a) = Q^{\pi}(s, a) - V^{\pi}(s)$$
$$\mathbb{E}_{a \sim \pi(\cdot|s)}[A^{\pi}(s, a)] = 0$$

Optimal Advantage Function Something

$$A(s, a) = Q(s, a) - V(s)$$

$$A(s, a^*) = 0, \quad a^* = \operatorname*{max}_a Q(s, a)$$

Proof. Before

$$V^{\pi}(s) = \mathbb{E}_{a \sim \pi(\cdot|s)}[Q^{\pi}(s, a)]$$

= $\mathbb{E}_{a \sim \pi(\cdot|s)}[A^{\pi}(s, a) + V^{\pi}(s)]$
= $\mathbb{E}_{a \sim \pi(\cdot|s)}[A^{\pi}(s, a)] + V^{\pi}(s)$

After.