

Double Q-Learning

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Reinforcement Learning class (COMP 767)

Optimal action-value function and Q-Learning

We are interested in finding the solution to the **Bellman equation**:

$$Q^*(s, a) = \sum_{s'} P_{sa}^{s'} \left(R_{sa}^{s'} + \gamma \max_b Q^*(s', b) \right)$$

One possible option – **Q-learning**:

$$Q_{t+1}(s, a) \leftarrow Q_t(s, a) + \alpha \left(r + \gamma \max_b Q_t(s', b) - Q_t(s, a) \right)$$

Major problem:

- Q-Learning **overestimates** Q^*
- Bias is accumulated at every update

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Why is that?

Q_t is a **noisy approximation** of Q^* .

In presence of noise we get:

$$\mathbb{E} \left[\max_b Q_t(s', b) \right] > \max_b \mathbb{E} [Q_t(s', b)]$$

That's because Q-Learning is based on a *so-called* **single estimator** for each variable (as opposed to the **double estimator** proposed in the paper).

The Single Estimator

Quite often (also in Q-Learning) we have a set of RVs $Z = \{Z_1, \dots, Z_M\}$ and we want to estimate:

$$\max_i \mathbb{E}[Z_i]$$

Say, we have a set of **unbiased** estimators $\{\mu_1, \dots, \mu_M\}$, s.t. $\mathbb{E}[\mu_i] = \mathbb{E}[Z_i]$. Then an obvious estimator is

$$\max_i \mu_i \approx \max_i \mathbb{E}[Z_i]$$

Turns out to be **positively biased**! From **Jensen's inequality**:

$$\mathbb{E} \left[\max_i \mu_i \right] \geq \max_i \mathbb{E}[\mu_i] = \max_i \mathbb{E}[Z_i]$$

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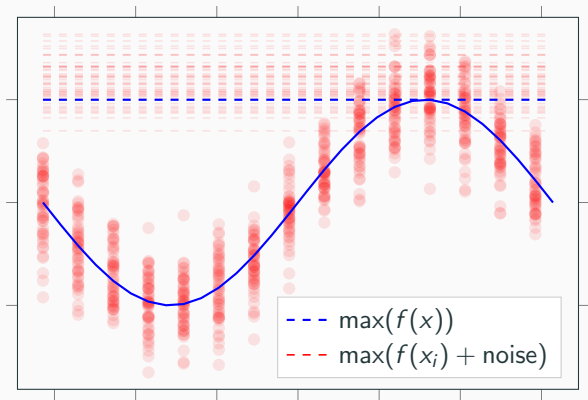
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So, often $\max_i \mu_i > \max_i \mathbb{E}[Z_i]$.

The Single Estimator (cont.)

Illustration:

- Let Z_i be deterministic $f(x_i)$ (blue curve)
- Let $\mu_i = f(x_i) + \text{noise}$ (an unbiased estimate of Z_i)



The Double Estimator

We tackle the overestimation by introducing **two sets of estimates**: $\mu^A = \{\mu_1^A, \dots, \mu_M^A\}$ and $\mu^B = \{\mu_1^B, \dots, \mu_M^B\}$:

- Obtained on two non-overlapping subsets of the samples \Rightarrow independent
- Both are unbiased: $\mathbb{E}[\mu_i^A] = \mathbb{E}[\mu_i^B] = \mathbb{E}[Z_i]$

The **proposed estimator**:

- Select maximizing argument from one set: $a^* = \arg \max_i \mu_i^A$
- Plug it into the other set: $\mu_{a^*}^B \approx \max_i \mathbb{E}[Z_i]$

The Double Estimator underestimates

Lemma

Let $\mathcal{M} = \{j \mid \mathbb{E}[Z_j] = \max_i \mathbb{E}[Z_i]\}$ be the set of elements that maximize the expected values. Let a^ be an element that maximizes μ^A . Then*

$$\mathbb{E} \left[\mu_{a^*}^B \right] = \mathbb{E} [Z_{a^*}] \leq \max_i \mathbb{E}[Z_i] .$$

Furthermore, the inequality is strict iff $\mathbb{P}[a^ \notin \mathcal{M}] > 0$.*

This lemma tells us that the Double Estimator has a **negative bias** (underestimates).

The Double Estimator underestimates (cont.)

Proof:

The maximizer a^* can be either in \mathcal{M} or not in \mathcal{M} (obviously):

Consider $a^* \in \mathcal{M}$, then

$$\begin{aligned}\mathbb{E} \left[\mu_{a^*}^B \mid a^* \in \mathcal{M} \right] &= \mathbb{E} \left[\sum_i \mu_i^B \mathbf{1}\{a^* = i\} \mid a^* \in \mathcal{M} \right] \\&= \sum_i \mathbb{E} \left[\mu_i^B \mid a^* \in \mathcal{M} \right] \cdot \mathbb{P}[a^* = i \mid a^* \in \mathcal{M}] \\&= \sum_i \mathbb{E} \left[\mu_i^B \right] \cdot \mathbb{P}[a^* = i \mid a^* \in \mathcal{M}] \\&= \sum_i \mathbb{E} [Z_i] \cdot \mathbb{P}[a^* = i \mid a^* \in \mathcal{M}] \\&= \mathbb{E} [Z_{a^*} \mid a^* \in \mathcal{M}] = \max_i \mathbb{E} [Z_i]\end{aligned}$$

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Now consider $a^* \notin \mathcal{M}$ and choose $j \in \mathcal{M}$, then

$$\mathbb{E} \left[\mu_{a^*}^B \mid a^* \notin \mathcal{M} \right] = \mathbb{E} [Z_{a^*} \mid a^* \notin \mathcal{M}] < \mathbb{E} [Z_j] = \max_i \mathbb{E} [Z_i]$$

Let's combine the expectations above:

$$\begin{aligned} \mathbb{E} \left[\mu_{a^*}^B \right] &= \mathbb{P} [a^* \in \mathcal{M}] \mathbb{E} \left[\mu_{a^*}^B \mid a^* \in \mathcal{M} \right] + \\ &\quad \mathbb{P} [a^* \notin \mathcal{M}] \mathbb{E} \left[\mu_{a^*}^B \mid a^* \notin \mathcal{M} \right] \\ &= \mathbb{P} [a^* \in \mathcal{M}] \max_i \mathbb{E} [Z_i] + \mathbb{P} [a^* \notin \mathcal{M}] \mathbb{E} \left[\mu_{a^*}^B \mid a^* \notin \mathcal{M} \right] \\ &\leq \mathbb{P} [a^* \in \mathcal{M}] \max_i \mathbb{E} [Z_i] + \mathbb{P} [a^* \notin \mathcal{M}] \max_i \mathbb{E} [Z_i] \\ &= \max_i \mathbb{E} [Z_i] \end{aligned}$$

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Double Q-Learning

Algorithm Double Q-Learning

```
1: Initialize  $Q^A(s, a)$  and  $Q^B(s, a)$ ,  $\forall s \in \mathcal{S}, a \in \mathcal{A}(s)$ 
2: for each episode do
3:   Initialize  $s$ 
4:   for each step of the episode do
5:     Choose  $a$  from  $s$  using policy derived from  $Q_A$  and  $Q_B$ 
6:     Take action  $a$ , observe  $r, s'$ 
7:     Toss a fair coin
8:     if heads then
9:        $Q^A(s, a) \leftarrow Q^A(s, a) + \alpha (r + \gamma Q^B(s', \arg \max_a Q^A(s', a)) - Q^A(s, a))$ 
10:    else
11:       $Q^B(s, a) \leftarrow Q^A(s, a) + \alpha (r + \gamma Q^A(s', \arg \max_a Q^B(s', a)) - Q^B(s, a))$ 
12:    end if
13:     $s \leftarrow s'$ 
14:  end for
15: end for
```
