

Double Q-Learning

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Q-Learning

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \left[R_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, A_t) \right]$$

- Disadvantages
 - **Overestimations** of the action values resulting from using the maximum value as approximation for the maximum expected value.

Double Q-Learning, Hasselt [2011]

- Randomly pick Q1 or Q2
 - Q1 updating

$$Q_1(S_t, A_t) \leftarrow Q_1(S_t, A_t) + \alpha \left(R_{t+1} + Q_2(S_{t+1}, \arg \max_a Q_1(S_{t+1}, a)) - Q_1(S_t, A_t) \right)$$

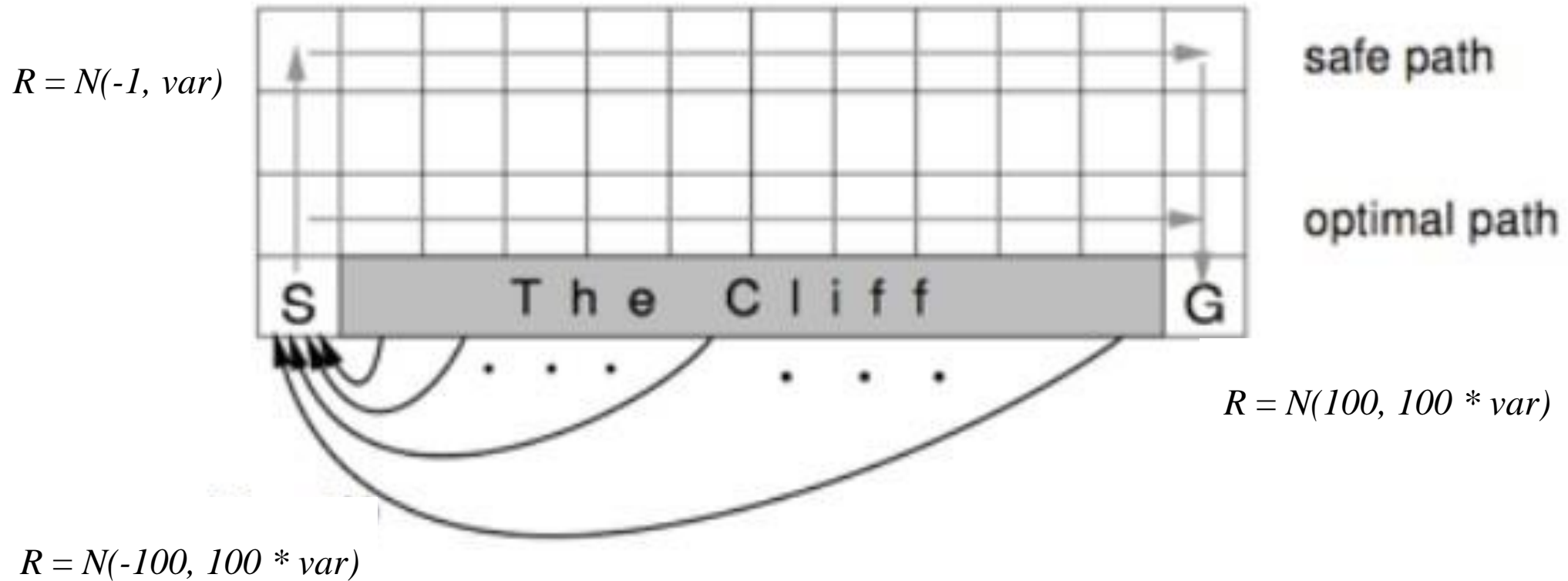
Double Q-Learning, Hasselt [2011]

Lemma 1. Let $X = \{X_1, \dots, X_M\}$ be a set of random variables and let $\mu^A = \{\mu_1^A, \dots, \mu_M^A\}$ and $\mu^B = \{\mu_1^B, \dots, \mu_M^B\}$ be two sets of unbiased estimators such that $E\{\mu_i^A\} = E\{\mu_i^B\} = E\{X_i\}$, for all i . Let $\mathcal{M} \stackrel{\text{def}}{=} \{j \mid E\{X_j\} = \max_i E\{X_i\}\}$ be the set of elements that maximize the expected values. Let a^* be an element that maximizes μ^A : $\mu_{a^*}^A = \max_i \mu_i^A$. Then $E\{\mu_{a^*}^B\} = E\{X_{a^*}\} \leq \max_i E\{X_i\}$. Furthermore, the inequality is strict if and only if $P(a^* \notin \mathcal{M}) > 0$.

Proof. Assume $a^* \in \mathcal{M}$. Then $E\{\mu_{a^*}^B\} = E\{X_{a^*}\} \stackrel{\text{def}}{=} \max_i E\{X_i\}$. Now assume $a^* \notin \mathcal{M}$ and choose $j \in \mathcal{M}$. Then $E\{\mu_{a^*}^B\} = E\{X_{a^*}\} < E\{X_j\} \stackrel{\text{def}}{=} \max_i E\{X_i\}$. These two possibilities are mutually exclusive, so the combined expectation can be expressed as

$$\begin{aligned} E\{\mu_{a^*}^B\} &= P(a^* \in \mathcal{M})E\{\mu_{a^*}^B \mid a^* \in \mathcal{M}\} + P(a^* \notin \mathcal{M})E\{\mu_{a^*}^B \mid a^* \notin \mathcal{M}\} \\ &= P(a^* \in \mathcal{M}) \max_i E\{X_i\} + P(a^* \notin \mathcal{M})E\{\mu_{a^*}^B \mid a^* \notin \mathcal{M}\} \\ &\leq P(a^* \in \mathcal{M}) \max_i E\{X_i\} + P(a^* \notin \mathcal{M}) \max_i E\{X_i\} = \max_i E\{X_i\} , \end{aligned}$$

Randomized Cliff Walking



Results

