## Q Learning

The goal of reinforcement learning is to compute an optimal policy  $\pi^*$ . As previously explained, the optimal policy can be easily computed from Q(s,a). The following algorithm can be used to compute Q(s,a).

**0.** Start with  $\hat{Q}$  as an estimate for Q. For example, for all states s and actions a set  $\hat{Q}(s,a)=0$ .

## 1. Repeat:

- **1.1** Select a state s and an action a.
- **1.2** Let r = r(s, a) be the reward.
- **1.3** Let  $s' = \delta(s, a)$  be the state one moves to from s if action a is taken.
- **1.4** Update:

$$\hat{Q}(s, a) = r + \gamma \max_{a'} \hat{Q}(s', a')$$

The method of selecting a state and an action at 1.1 is arbitrary. The algorithm is guaranteed to converge to the right Q if each (s, a) pair is visited infinitely many times.

## Convergence

Let t be the iteration number. In terms of t the iteration in 1.4 can be written as:

$$\hat{Q}_{t+1}(s, a) = r + \gamma \max_{a'} \hat{Q}_t(s', a')$$

Consider the following error terms:

$$e_t(s, a) = |\hat{Q}_t(s, a) - Q(s, a)|$$

$$e_t(s) = \max_a e_t(s, a)$$

$$e_t = \max_s e_t(s)$$

$$= \max_{s, a} |\hat{Q}_t(s, a) - Q(s, a)|$$

At iteration t the algorithm selects s, a, computes r, s', and updates  $\hat{Q}(s, a)$ . The key technical lemma here states that:

$$e_{t+1}(s,a) \le \gamma e_t$$

Proof:

$$\begin{aligned} e_{t+1}(s, a) &= |\hat{Q}_{t+1}(s, a) - Q(s, a)| \\ &= |(r + \gamma(\max_{a'} \hat{Q}_{t}(s', a')) - (r + \gamma(\max_{a'} Q(s', a'))|) \\ &= \gamma|\max_{a'} \hat{Q}_{t}(s', a') - \max_{a'} Q(s', a')| \\ &\leq \gamma \max_{a'} |\hat{Q}_{t}(s', a') - Q(s', a')| \\ &= \gamma \max_{a'} e_{t}(s', a') \\ &\leq \gamma e_{t} \end{aligned}$$

The inequality between the third and the fourth line is:

$$\left| \max_{a} f(a) - \max_{a} g(a) \right| \le \max_{a} |f(a) - g(a)|$$

It follows from the triangle inequality in the  $l_{\infty}$  norm, and can also be easily proved directly.

The value of  $e_t(s, a)$  is not guaranteed to decrease as a function of t, and may even increase. But as shown below the value of  $e_t$  cannot increase. It is guaranteed to decrease by a factor of  $\gamma$  in a cycle where all (s, a) pairs are visited. The first observation is that for *all* pairs s, a:

$$e_{t+j}(s,a) \le e_t$$
 for  $j \ge 0$ 

For the proof it is enough to show that it holds for j = 1, and then apply induction. The case j = 1 follows from the lemma. Now consider the relation between the error at iteration t and the error at iteration  $t + \Delta$ . We can make the following observations:

- **1.**  $e_{t+j} \le e_t \text{ for } j = 0, 1, \dots, \Delta.$
- **2.**  $e_{t+\Delta}(s,a) \leq \gamma \ e_t$  for all (s,a) that were visited in the  $\Delta$  iterations.
- **3.**  $e_{t+\Delta} \leq \gamma \ e_t$  if all (s,a) were visited in the  $\Delta$  iterations.

**Conclusion:**  $\hat{Q}(s,a)$  approaches Q(s,a) if each (s,a) is visited infinitely many times.