

Reward Shaping

Adds a small reward for each transition

based on domain knowledge to encourage

positive actions (like a heuristic)

$$Q(s,a) = Q(s,a) + \alpha [r + \underset{\substack{\uparrow \\ \text{shaped reward}}}{F(s,s')} + \gamma Q(s',a') - Q(s,a)]$$

Potential Based Reward Shaping

Potential function $\Phi(s)$: Basically a heuristic for

state s larger value means state is better

can calculate shaped reward with Φ

$$F(s,s') = \gamma \Phi(s') - \Phi(s)$$

• Using potential function guarantees alg will

learn optimal policy

• However, no guarantee that it will converge faster

$$E[X] = \sum P(x) \cdot x$$

$$[V]$$

Policy Iteration

Evaluates the value of policies directly

Improves the policy over time

2 steps during each iteration:

1) policy evaluation

2) policy improvement

• Repeat until policy converges

Policy evaluation

Find the value of each state $V^\pi(s)$ under the

current policy

Algorithm - Policy evaluation

Input: π the policy for evaluation, V^π value function, and MDP $M = \langle S, s_0, A, P_a(s' | s), r(s, a, s') \rangle$

Output: Value function V^π

Repeat

$\Delta \leftarrow 0$

For each $s \in S$

$$V^{\pi}(s) \leftarrow \sum_{s' \in S} P_{\pi(s)}(s' | s) [r(s, a, s') + \gamma V^{\pi}(s')] \quad V(s) \text{ based only on policy action}$$

Policy evaluation equation

$$\Delta \leftarrow \max(\Delta, |V^{\pi}(s) - V^{\pi}(s)|)$$

$V^\pi \leftarrow V^{\pi}$

Until $\Delta \leq \theta$ until convergence

1st done by hand: Use a table Or solve simultaneous equations

eg)

Stone Policy

$$\begin{array}{ccc} \pi(s_0) & \pi(s_1) & \pi(s_2) \\ a_0 & a_1 & a_2 \end{array}$$

	$V(s_0)$	$V(s_1)$	$V(s_2)$	
Init	0	0	0	
1	2	-1	3	values on each line depend on
2	1	-2	4	values in prev line
3	0.5	-2.7	4.3	
4	0.5	-2.7	4.3	until 2 lines are the same (or close enough)

Once $V^\pi(s)$ found for all states, move to policy Improvement

Policy Improvement

- 1) Calculate $Q(s, a)$ for all actions a in state s
- 2) Set policy for s $\pi(s) = \text{action with highest } Q(s, a)$
- 3) Repeat for all states

$$Q^\pi(s, a) = \sum_{s' \in S} P_a(s' | s) [r(s, a, s') + \gamma \underline{V^\pi(s')}] \quad V^\pi(s') \text{ from the table}$$

$$Q^\pi(s, a) = \sum_{s' \in S} P_a(s' | s) [r(s, a, s') + \gamma \underbrace{V^\pi(s')}_{V^\pi(s) \text{ from the table}}]$$

Put Together

Algorithm - Policy Iteration

Input: MDP $M = \langle S, s_0, A, P_a(s' | s), r(s, a, s') \rangle$

Output: Policy π

Set V^π to arbitrary value function; e.g., $V^\pi(s) = 0$ for all s .

Set π to arbitrary policy; e.g. $\pi(s) = a$ for all s , where $a \in A$ is an arbitrary action.

Repeat

 Compute $V^\pi(s)$ for all s using policy evaluation

For each $s \in S$

$\pi(s) \leftarrow \operatorname{argmax}_{a \in A(s)} Q^\pi(s, a)$

Until π does not change