HW4: Reinforcement Learning

CS6300: Artificial Intelligence **Jake Pitkin**
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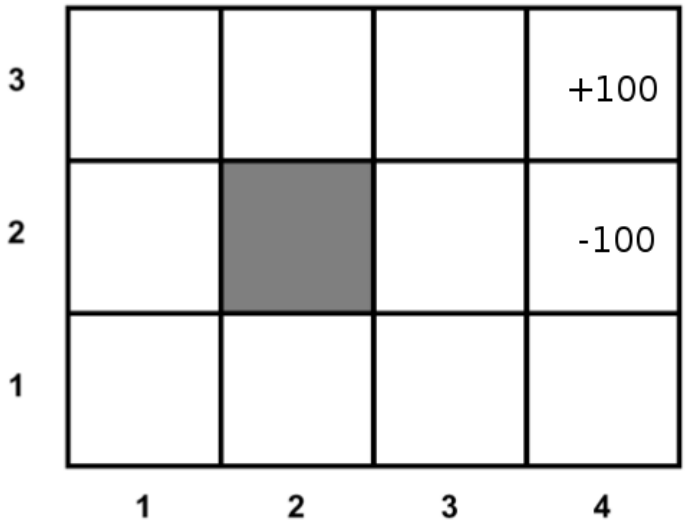
1 TD and Q in Blockworld

Consider the following gridworld:



Suppose that we run two episodes that yield the following sequences of (state, action, reward) tuples:

S	A	R	S	A	R
(1,1)	up	-1	(1,1)	up	-1
(2,1)	left	-1	(1,2)	up	-1
(1,1)	up	-1	(1,3)	right	-1
(1,2)	up	-1	(2,3)	right	-1
(1,3)	up	-1	(2,3)	right	-1
(2,3)	right	-1	(3,3)	right	-1
(3,3)	right	-1	(4,3)	exit	+100
(4,3)	exit	+100	(done)		
(done)					

1. **According to direct estimation, what are the values for every state in the grid?**

State	Calculation	Value
(1,1)	(93 + 95 + 94)/3	93.666
(1,2)	(96 + 95)/2	95.5
(1,3)	(97 + 96)/2	96.5
(2,1)	94/1	94
(2,2)	-	-
(2,3)	(98 + 97 + 98)/3	97.666
(3,1)	-	-
(3,2)	-	-
(3,3)	(99 + 99)/2	99
(4,1)	-	-
(4,2)	-	-
(4,3)	(100 + 100/2	100

2. **According to model-based learning, what are the transition probabilities for every (state, action, state) triple. Don't bother listing all the ones that we have no information about.**

s	a	s′	T(s, a, s′)
(1,1)	up	(2,1)	1/3
(2,1)	left	(1,1)	1
(1,1)	up	(1,2)	2/3

3. **Suppose that we run Q-learning. However, instead of initializing all our Q values to zero, we initialize them to some large positive number ("large" with respect to the maximum reward possible in the world: say, 10 times the max reward). I claim that this will cause a Q-learning agent to initially explore a lot and then eventually start exploiting. Why should this be true? Justify your answer in a short paragraph.**

2 Policy Gradient

In order to do policy gradient, we need to be able to compute the gradient of the value function J with respect to a parameter vector θ: $\nabla_\theta J(\theta)$. By our algebraic magic, we expressed this as:

$$\nabla_\theta J(\theta) = \sum_a \pi_\theta(s_0, a) R(a) \underbrace{\nabla_\theta \log\left(\pi_\theta(s_0, a)\right)}_{g(s_0,a)} \tag{1}$$

If we us a linear function thrown through a soft-max as our stochastic policy, we have:

$$\pi_\theta(s, a) = \frac{\exp\left(\sum_{i=1}^n \theta_i f_i(s, a)\right)}{\sum_{a'} \exp\left(\sum_{i=1}^n \theta_i f_i(s, a')\right)} \tag{2}$$

Compute a closed form solution for $g(s_0, a)$. Explain in a few sentences *why* this leads to a sensible update for gradience ascent (i.e., if we plug this in to Eq (1) and do gradient ascent, why is the derived form reasonable)?