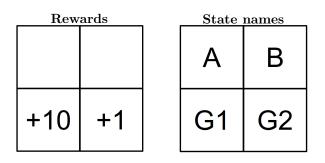
## Regular Discussion 10

## 1 Q-learning

Consider the following gridworld (rewards shown on left, state names shown on right).



From state A, the possible actions are right( $\rightarrow$ ) and down( $\downarrow$ ). From state B, the possible actions are left( $\leftarrow$ ) and down( $\downarrow$ ). For a numbered state (G1, G2), the only action is to exit. Upon exiting from a numbered square we collect the reward specified by the number on the square and enter the end-of-game absorbing state X. We also know that the discount factor  $\gamma = 1$ , and in this MDP all actions are **deterministic** and always succeed.

Consider the following episodes:

Episode 1 $(E1)$				Episode 2 ( $E2$ )			<b>Episode 3</b> (E3)				Episode 4 $(E4)$				
	a	<u> </u>	<u>_</u>		a		<u>~)</u>	s	a	s'	r	s	a	s'	r
3		3	-			3	/	A	$\rightarrow$	B	0	B	$\leftarrow$	A	0
A	↓.	GI	10	B	↓.	G2	0	B	$\downarrow$	G2	0	A	$\downarrow$	G1	0
GI	exit	X	10	G2	exit	X	1	G2	exit	X	1	G1	exit	X	10

(a) Consider using temporal-difference learning to learn V(s). When running TD-learning, all values are initialized to zero.

For which sequences of episodes, if repeated infinitely often, does V(s) converge to  $V^*(s)$  for all states s?

(Assume appropriate learning rates such that all values converge.)

Write the correct sequence under "Other" if no correct sequences of episodes are listed.



Other \_\_\_\_\_

(b) Consider using Q-learning to learn Q(s, a). When running Q-learning, all values are initialized to zero. For which sequences of episodes, if repeated infinitely often, does Q(s, a) converge to  $Q^*(s, a)$  for all stateaction pairs (s, a)

 $\begin{array}{c|c} (\text{Assume appropriate learning rates such that all Q-values converge.}) \\ \text{Write the correct sequence under "Other" if no correct sequences of episodes are listed.} \\ \hline & E1, E2, E3, E4 & \Box & E1, E2, E1, E2 & \Box & E1, E2, E3, E1 & \Box & E4, E4, E4, E4 \\ \hline & E4, E3, E2, E1 & \Box & E3, E4, E3, E4 & \Box & E1, E2, E4, E1 \\ \end{array}$ 

Other \_\_\_\_\_

## 2 Pacman with Feature-Based Q-Learning

We would like to use a Q-learning agent for Pacman, but the size of the state space for a large grid is too massive to hold in memory. To solve this, we will switch to feature-based representation of Pacman's state.

(a) We will have two features,  $F_g$  and  $F_p$ , defined as follows:

$$F_g(s,a) = A(s) + B(s,a) + C(s,a)$$
  
$$F_p(s,a) = D(s) + 2E(s,a)$$

where

A(s) = number of ghosts within 1 step of state s

B(s, a) = number of ghosts Pacman touches after taking action a from state s

C(s, a) = number of ghosts within 1 step of the state Pacman ends up in after taking action a

D(s) = number of food pellets within 1 step of state s

E(s, a) = number of food pellets eaten after taking action a from state s

For this pacman board, the ghosts will always be stationary, and the action space is {left, right, up, down, stay}.

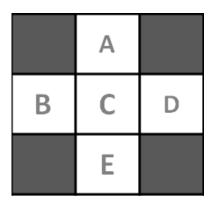


calculate the features for the actions  $\in \{left, right, up, stay\}$ 

- (b) After a few episodes of Q-learning, the weights are  $w_g = -10$  and  $w_p = 100$ . Calculate the Q value for each action  $\in \{left, right, up, stay\}$  from the current state shown in the figure.
- (c) We observe a transition that starts from the state above, s, takes action up, ends in state s' (the state with the food pellet above) and receives a reward R(s, a, s') = 250. The available actions from state s' are down and stay. Assuming a discount of  $\gamma = 0.5$ , calculate the new estimate of the Q value for s based on this episode.
- (d) With this new estimate and a learning rate ( $\alpha$ ) of 0.5, update the weights for each feature.

## 3 Learning in Gridworld

Consider the example gridworld that we looked at in lecture. We would like to use TD learning and q-learning to find the values of these states.



Suppose that we have the following observed transitions: (B, East, C, 2), (C, South, E, 4), (C, East, A, 6), (B, East, C, 2)

The initial value of each state is 0. Assume that  $\gamma = 1$  and  $\alpha = 0.5$ .

(a) What are the learned values from TD learning after all four observations?

(b) What are the learned Q-values from Q-learning after all four observations?