# Exam Prep 5

## Q1. RL

Pacman is in an unknown MDP where there are three states [A, B, C] and two actions [Stop, Go]. We are given the following samples generated from taking actions in the unknown MDP. For the following problems, assume $\gamma = 1$ and $\alpha = 0.5$.

**(a)** We run Q-learning on the following samples:

| **s** | **a** | **s'** | **r** |
|---|---|---|---|
| A | Go | B | 2 |
| C | Stop | A | 0 |
| B | Stop | A | -2 |
| B | Go | C | -6 |
| C | Go | A | 2 |
| A | Go | A | -2 |

What are the estimates for the following Q-values as obtained by Q-learning? All Q-values are initialized to 0.

**(i)** $Q(C, Stop) =$ ______________________

**(ii)** $Q(C, Go) =$ ______________________

**(b)** For this next part, we will switch to a feature based representation. We will use two features:

- $f_1(s, a) = 1$
- $f_2(s, a) = \begin{cases} 1 & a = \text{Go} \\ -1 & a = \text{Stop} \end{cases}$

Starting from initial weights of 0, compute the updated weights after observing the following samples:

| **s** | **a** | **s'** | **r** |
|---|---|---|---|
| A | Go | B | 4 |
| B | Stop | A | 0 |

What are the weights after the first update? (using the first sample)

**(i)** $w_1 =$ ______________________

**(ii)** $w_2 =$ ______________________

What are the weights after the second update? (using the second sample)

**(iii)** $w_1 =$ ______________________

**(iv)** $w_2 =$ ______________________

# Q2. Reinforcement Learning

**(a)** Each True/False question is worth 1 points. Leaving a question blank is worth 0 points. **Answering incorrectly is worth $-1$ points.**

**(i)** [*true* or *false*] Temporal difference learning is an online learning method.

**(ii)** [*true* or *false*] Q-learning: Using an optimal exploration function leads to no regret while learning the optimal policy.

**(iii)** [*true* or *false*] In a deterministic MDP (i.e. one in which each state / action leads to a single deterministic next state), the Q-learning update with a learning rate of $\alpha = 1$ will correctly learn the optimal q-values (assume that all state/action pairs are visited sufficiently often).

**(iv)** [*true* or *false*] A small discount (close to 0) encourages greedy behavior.

**(v)** [*true* or *false*] A large, negative living reward ($\ll 0$) encourages greedy behavior.

**(vi)** [*true* or *false*] A negative living reward can always be expressed using a discount $< 1$.

**(vii)** [*true* or *false*] A discount $< 1$ can always be expressed as a negative living reward.

**(b)** Given the following table of $Q$-values for the state $A$ and the set of actions $\{Forward, Reverse, Stop\}$, what is the probability that we will take each action on our next move when we following an $\epsilon$-greedy exploration policy (assuming any random movements are chosen uniformly from all actions)?

$Q(A, Forward) = 0.75$
$Q(A, Reverse) = 0.25$
$Q(A, Stop) = 0.5$

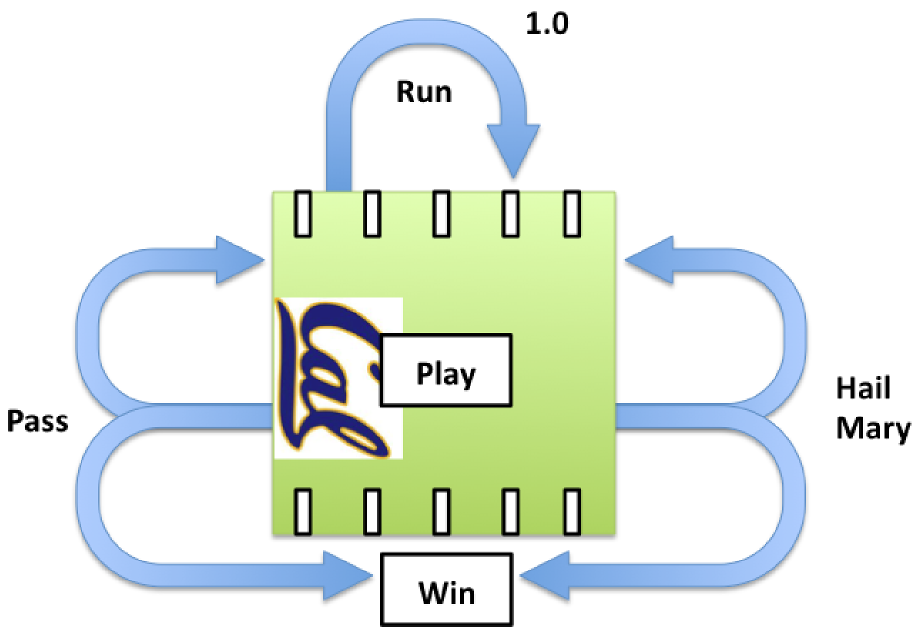
| Action | Probability (in terms of $\epsilon$) |
|---|---|
| $Forward$ | |
| $Reverse$ | |
| $Stop$ | |

# Q3. MDPs and RL: Go Bears!

Cal's Football team is playing against UCLA for the big homecoming game Saturday night. With a lot of losses in the season so far, Cal needs to switch up their strategy to get any hope of winning this game.

Luckily, the Quarterback (Joe) is a star student in CS188 and has decided to model the game as a Markov Decision Process. There are only two states – the *Play* state (shown as the field in the diagram) and the *Win* State. Although the connectivity of the states is known, the probabilities for each are not.

There are no actions available from the *Win* state – the game simply ends.




From the *Play* state there are three actions: *Run*, *Pass*, and *HailMary*. The connectivity of each action to the two states is shown above.

Reward Values:

| State | Action | State' | R(s,a,s') |
|---|---|---|---|
| Play | Run | Play | 2 |
| Play | Pass | Play | 4 |
| Play | Pass | Win | 10 |
| Play | Hail Mary | Play | 0 |
| Play | Hail Mary | Win | 100 |

**(a) Learning Values** Joe wants to learn the value of the play state so he can estimate the outcome of the game. He uses a discount factor of 0.5 for all questions below.

**(i)** Joe first uses temporal difference value learning to learn the value of the *play* state. After initializing his beliefs to 0, he sees two episodes while in tape review. With a learning rate $\alpha$ of 0.5 what value of the state *play* does he learn?

| State | Action | State' |
|---|---|---|
| Play | Run | Play |
| Play | Hail Mary | Play |

$$V(play) =$$

**(ii)** Coach Tedford decides to give Joe a fixed policy instead:

$$\pi(s) \quad = \quad Run$$

What value for the state *play* would Joe calculate if he ran value iteration until convergence? Keep in mind that $\sum_{n=0}^{\infty}(\frac{1}{2})^n = 2 - (\frac{1}{2})^n = 1 + 0.5 + 0.25 + 0.125 + ...$

$$V^{\pi}(play) \quad =$$

**(b)** **Game Time** Joe watches the next lecture video from class and now wants to use Q-learning to compute his optimal strategy.

**(i)** First Joe uses temporal difference Q-learning to learn the values of the Q nodes. He sees three episodes during the first quarter:

| State | Action | State' |
|---|---|---|
| Play | Run | Play |
| Play | Hail Mary | Play |
| Play | Pass | Win |

Update the Q node values after processing each episode (in order). Use a learning rate of 0.5 and a discount rate of 0.5.

| State | Action | $Q(s,a)$ |
|---|---|---|
| Play | Run | |
| Play | Hail Mary | |
| Play | Pass | |

**(c)** Q learning is going well, but it's taking too much time. Thankfully Oski shows up with some special information – he has watched so many games that he know's the true transition probabilities! Here they are:

| State | Action | State' | R(s,a,s') | T(s,a,s') |
|---|---|---|---|---|
| Play | Run | Play | 2 | 1.0 |
| Play | Pass | Play | 4 | 0.5 |
| Play | Pass | Win | 10 | 0.5 |
| Play | Hail Mary | Play | 0 | 0.9 |
| Play | Hail Mary | Win | 100 | 0.1 |

**(i)** Now with these probabilities, what is the optimal policy when there is one time step left? The value?

$$\pi_{k=1}(play) =$$

$$V_{k=1}(play) =$$

**(ii)** For two time steps left, what is the optimal policy with discount factor 0.5? Hint: you can use your value above to aid in this computation.

$$\pi_{k=2}(play) =$$

$$V_{k=2}(play) =$$