Homework 3
CS3316 Reinforce learning

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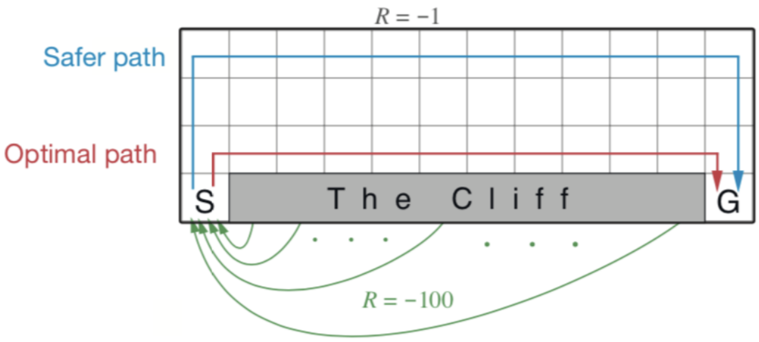
Architecture

We design the program to take in the gridworld but with a cliff. This time the starting position is fixed, and the agent has to navigate to the goal state on the opposite end of the map.



The agent can take multiple paths to the goal state as shown in the image. If the agent however, steps into the cliff, he will fall and return to the start point and receive a reward of -100. Ideally, the agent will take the path closest to the cliff to the goal, to minimize the negative rewards that he receives. We will see in the following 2 algorithm how the model performs and what we can infer from the learning.

SARSA

Sarsa (on-policy TD control) for estimating $Q \approx q_*$

Algorithm parameters: step size $\alpha \in (0, 1]$, small $\varepsilon > 0$
Initialize $Q(s, a)$, for all $s \in \mathcal{S}^+, a \in \mathcal{A}(s)$, arbitrarily except that $Q(\textit{terminal}, \cdot) = 0$

Loop for each episode:
  Initialize S
  Choose A from S using policy derived from Q (e.g., ε-greedy)
  Loop for each step of episode:
    Take action A, observe R, S'
    Choose A' from S' using policy derived from Q (e.g., ε-greedy)
    $Q(S, A) \leftarrow Q(S, A) + \alpha\big[R + \gamma Q(S', A') - Q(S, A)\big]$
    $S \leftarrow S'$; $A \leftarrow A'$;
  until S is terminal

From SARSA, we can see that the agent is learning on policy. This means that the agent is learning the value of the policy that it is currently following. This is done by looking at the next state and the action that the agent will take in the next state. The agent will then update the quality of the current state and action based on the reward it receives and the quality of the next state and action.

```python
s = self.grid.state
action = self.get_action()
steps = 0
while not self.grid.is_finish() and steps < self.run_limit:
    s_prime, reward = self.grid.next_step_and_reward(action)
    # on policy learning
    action_prime = self.get_action()
    self.quality[(s,action)] += \
            self.alpha * (
                reward + \
                self.gamma * self.quality[(s_prime,action_prime)]\
                - self.quality[(s,action)]
            )
    action = action_prime
    s = s_prime
```

Listing 1: SARSA code

Q Learning

Q-learning (off-policy TD control) for estimating $\pi \approx \pi_*$

Algorithm parameters: step size $\alpha \in (0, 1]$, small $\varepsilon > 0$
Initialize $Q(s, a)$, for all $s \in \mathcal{S}^+, a \in \mathcal{A}(s)$, arbitrarily except that $Q(terminal, \cdot) = 0$

Loop for each episode:
  Initialize S
  Loop for each step of episode:
    Choose A from S using policy derived from Q (e.g., ε-greedy)
    Take action A, observe R, S'
    $Q(S, A) \leftarrow Q(S, A) + \alpha\big[R + \gamma \max_a Q(S', a) - Q(S, A)\big]$
    $S \leftarrow S'$
  until S is terminal

We implement the above algorithm and we note that this is different from SARSA where by the agent will always take the action that gives the maximum reward. This is because the agent is not looking at the next state but the maximum reward it can get from the next state.

```
s = self.grid.state
action = self.get_action()
s_prime, reward = self.grid.next_step_and_reward(action)
self.quality[(s,action)] += \
        self.alpha * (
            reward + \
            self.gamma *
            max([self.quality[(s_prime,a)] for a in self.grid.action])\
            - self.quality[(s,action)]
        )
```

Listing 2: Qlearning code

Results

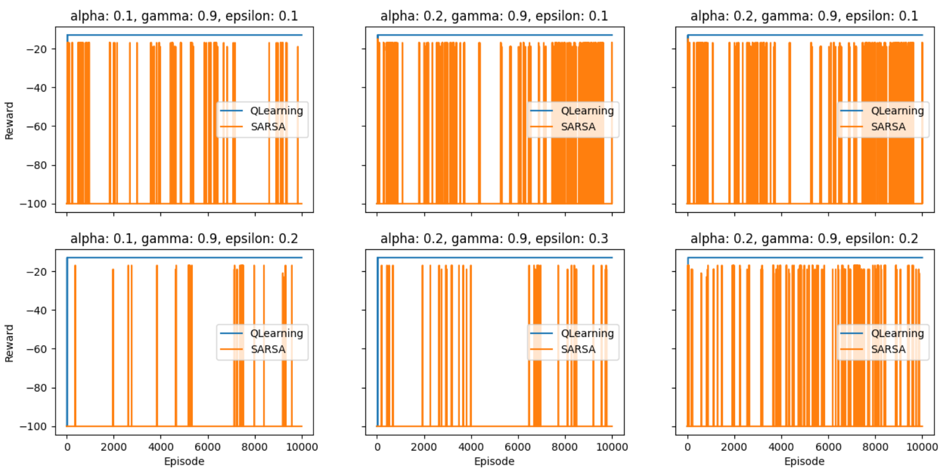


Figure 1: Performance of models based on different parameters

We can see that the Q learning algorithm has a higher average reward than the SARSA algorithm. For different paramters, we can see that the Q learning quickly converges to the optimal path while the SARSA algorithm takes a more conservative approach. We also note that the SARSA algorithm reaches a state where by the optimal path perceived is the safest path. This is the route that is the furthest alway from the cliff. This is interesting as for different parameters, especially with higher epsilon values, the agent should be exploring but it still takes the safest path.

If we however, decrease the epsilon then both methods would asymptotically converge to the optimal path. This is because the agent is not exploring and taking the optimal path.

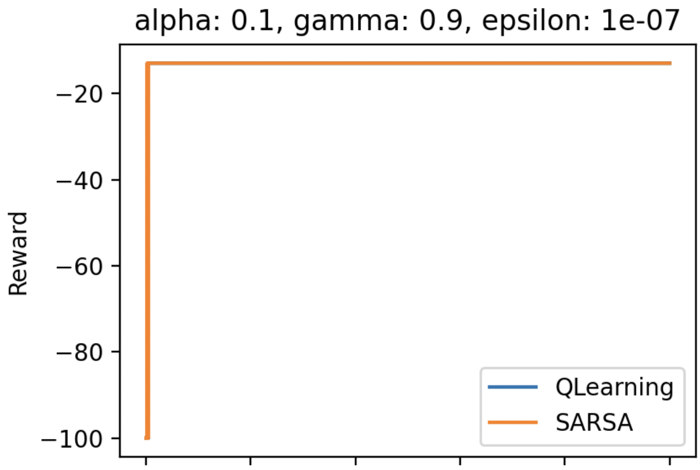


Figure 2: Parameters to achieve optimal path

Conclusion

From our SARSA algorithm, we can see that the agent always takes a more conservative apporach through a one step look ahead. This allows

While Q learning algorithm is more aggressive in its approach. Instead of looking one step ahead, it looks at the maximum reward it can get from the next state. This allows the agent to take more risks and explore the gridworld. Thus, we can see that when the agents reach their steady states, the Q learning algorithm has a higher average reward than the SARSA algorithm (less negative).

However, as we saw, with a sufficiently low epsilon, both algorithms will converge to the optimal path. This indicates that a low exploration but extreme greedy approach will force the agent to take the optimal path..