Evaluation of Sarsa(λ) Learning Agent

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I. Introduction

One of the most important reinforcement learning techniques we have learned in CSE 571 is Q-learning which learns through experience to arrive at a good policy. Q-learning does not require a complete model of the environment and can handle problem without requiring adaptations, only with with stochastic transitions and rewards. Q-learning has its drawbacks, however, one in particular being that it must remember every state that the agent has ever been in, as well as the possible actions in that state. This is a memory structure which grows exponentially with the number of other agents in the state space, and so we learned another technique: Approximate Q-learning, which reduces the state space via a set of applicable features, allowing us to have amuch smaller Q-table and fill it in a much smaller number of episodes. By successfully implementing the agent in our individual project 3, we have already had a good understanding of this method, however, it also has its limitations. For example, for whatever your approximation function is, the agent must wander into a goal, and continue wandering into the path leading to the goal, for each state in the path, building its Q table vector by vector. Eligibility Tracing offers an alternative to this, instead of updating only one state on transition, SARSA(λ) updates all vectors visited throughout the episode.

SARSA is similar to Q-learning, the only difference being that SARSA observes the action that the agent will choose in the next state that it visits, and SARSA(λ) is the SARSA algorithm with eligibility tracing.

In this group project, we compare approximate SARSA(λ) and approximate Q-learning.

II. Background

The Sarsa algorithm belongs to an On-Policy algorithm for TD-Learning. The speciality of this algorithm compared to Q-Learning is that in the next state, maximum reward doesnt play an role for updating the Q-values. Instead, it uses the next action and the same policy that determined the original action to get new reward. The name Sarsa actually comes from the four first letter of Q(s, a, r, s', a'). s and a represent original state and action, r is the reward observed in the following state, s', a' are the new state-action pair. As you can see in the following pictures, two action selection steps needed for determining the next state-action pair along with the first. The parameters a and r wont change as they do in Q-Learning. The nature of the policy's dependence on $\mathcal{Q}$ determine the convergence of the properties of Sarsa algorithm. For example, one could use ϵ-soft or ϵ-greedy policies. [2]

Initialize $Q(s,a) = 0$ for all $s \in \mathcal{S}, a \in \mathcal{A}(s)$
for *each episode* **do**
  $E(s,a) = 0$ for all $s \in \mathcal{S}, a \in \mathcal{A}(s)$
  Initialize S, A
  for *step in an episode* **do**
    Take action A and observe S', R
    Choose A' based on S' and current policy
    $\delta \leftarrow R + \gamma Q(S', A') - Q(S, A)$
    $E(S, A) \leftarrow (1 - \alpha)E(S, A) + 1$
    for *all* $s \in \mathcal{S}, a \in \mathcal{A}(s)$ **do**
      $Q(s,a) \leftarrow Q(s,a) + \alpha\delta E(s,a)$
      $E(s,a) \leftarrow \gamma\lambda E(s,a)$
    end
    $S \leftarrow S'$
    $A \leftarrow A'$
  end
  Until S is terminal
end

Algorithm 1: Sarsa(λ) Algorithm with Dutch Tracing. Algorithm was provided by Sutton et al. [2]

III. SARSA(λ) Implementation

We chose to start with the codebase provided by UC Berkeleys Pacman-themed AI tutorial, and compare the SARSA(λ) algorithm to the Q-learning algorithm without eligibility tracing. As the SARSA(λ) algorithm requires an eligibility trace we implemented this as a python dict with default value of 0, same as our Q table. Unlike the Q-table, the eligibility trace must be cleared between episodes, so we implemented a check for final step in the function which updated our Q table to clear the eligibility trace. To test and demo the SARSA(λ) agent, we used a test that was built-in, and used by UC berkeley which consisted of a small, gridworld maze for our agent to run around in. What we found was that while the Default q agent first had to random walk to the goal, then to the square in front of the goal, and so on for each episode, the SARSA(λ) agent converged very quickly. After a single random walk to the goal, the Q table updated almost immediately to the optimal policy for the default starting position. While we probably could have improved the results by implementing an ϵ-greedy

```
def update(self, state, action, nextState, reward):
    nextAction = self.getAction(nextState)

    delta = reward + (self.discount *
        self.values[(nextState, nextAction)]) -
        self.values[(state, action)]

    self.eligibility[(state, action)] = (1 - self.alpha) *
        self.eligibility[(state, action)] + 1

    for k, v in self.values.iteritems():
        trace = self.eligibility[k]
        self.values[k] = v + (self.alpha * delta * trace)
        self.eligibility[k] = trace * self.discount * self.y

    if not self.getLegalActions(nextState):
        self.eligibility = util.Counter()
```

Fig. 1: Implementation of `update` for Sarsa(λ) agent. Since `update` is called by the agent each time an aciton is selected, the function implements the inner loop of the algorithm detailed in Algorithm 1.

function, our results for the basic set learning rate worked very well.

IV. Results

Once the Sarsa(λ) agent had been integrated into the UC Berkley Pacman framework [1], *gridword.py* and *pacman.py* were used to test out the efficacy of the Sarsa(λ) agent compared to the Q-learning agent already present.

For the this paper, we evaluated policy/value convergence in *gridworld.py*, using the BookGrid world. Convergence was found by exponentially increasing the number of training episodes until the policy became stationary. The default values for each agent were: $\epsilon = 0.05, \gamma = 0.8, \alpha = 0.2\, \lambda = 0.8$ and $noise = 0.2$.

We also created two custom grid layouts visualizations. CustomGrid and LargeMazeGrid to test and compare the two agents. The LargeMazeGrid is a 20x20 grid with multiple dead ends and a single reward. We ran both the agents for 100 episodes (with default values and 0 noise) and the Sarsa(λ) agent out performed the Q-learning agent on this grid. For the Sarsa(λ) agent policy convergence was noticed after 15 episodes, whereas for the Q-learning agent it was after 65 episodes. Average time taken per episode for the Sarsa(λ) agent was 0.18s, while the Q-learning agent took 0.29s.

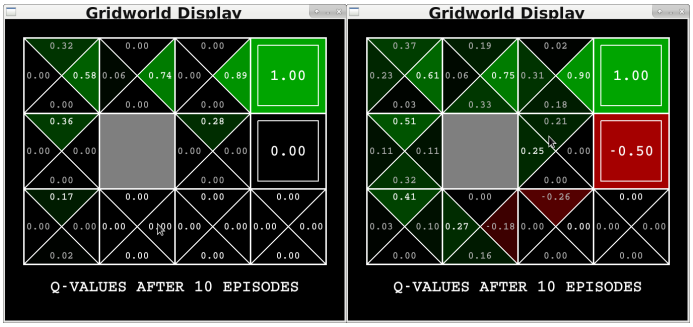
The CustomGrid is a 5x5 grid, with a small reward near the start point and a large reward further away, with a couple hazards along the way. We ran both the agents for 1000 episodes (with default values and 0 noise). Both the agents performed identically on this grid. With the small reward being near the start, both the agents deviated towards it and didn't stray much from that path.

To evaluate each agent in a more complex environment, we used *pacman.py* with smallGrid world. Each agent was trained for $[100, 2000]$ episodes and then evaluated for another 20 episodes. The default settings for each agent was: $\epsilon = 0.05, \gamma = 0.8, \alpha = 0.2$ and $\lambda = 0.8$.

Agent	Time(s)/100 eps	50% Win Rate	Value convergence
Sarsa(λ)	1678.92s	1000 eps	256 eps
Q-Learning	3.54s	800 eps	4096 eps
Approximate Q-Learning	1.92s	800 eps	N/A
Approximate Sarsaλ)	896.32s	1200 eps	N/A

TABLE I: Summary of measured differences between Sarsa(λ) and Q-learning agents. Time per 100 episodes (seconds) was taken from 20 trials using the *pacman.py* smallGrid world. Similarly, the agents were trained on an increasing number of episodes until they achieved a 50% win rate in the *pacman.py* smallGrid world. Value convergence was found by exponentially increasing the number of training episodes until the Q-values and action policy became stationary. Value convergence was run using *gridworld.py* on the BookGrid world.

Table I shows a summary of the experimental results. In general we found that the Sarsa(λ) agent out performed the Q-learning agent in the grid world. Sarsa(λ) was able to converge on an optimal policy 3840 training episodes before the Q- learning agent. On the other hand, the Sarsa(λ) agent took approximately 500$\times$ longer to train in the *pacman.py* environment, most likely due the number of $(state, action)$ pairs that exist in the environment. If we are willing to wait for the training rounds, the Sarsa(λ) agent was able to reach a consistent 100% win rate before the Q-learning agent.

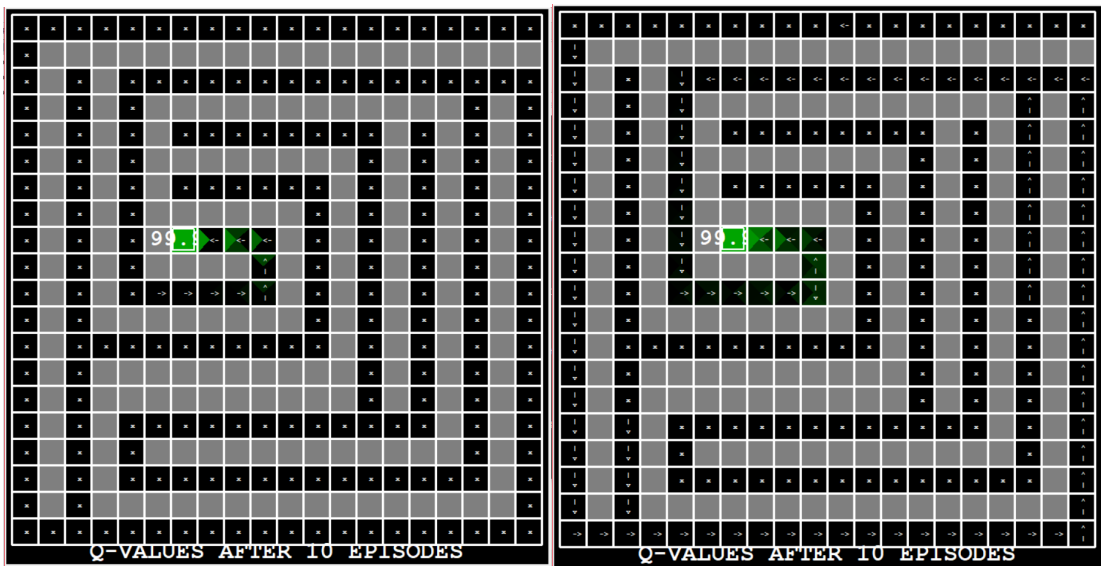


(a) Q-learning agent Q values (b) Sarsa(λ) agent Q values

Fig. 2: Q values of the Q-learning and Sarsa(λ) agents after 10 episodes of training. The Sarsa(λ) agent is able to evaluate more of the state space than the Q-learning agent. Each agent was run for 10 episodes on the BookGrid world with a noise rate of 0.2, and $\epsilon = 0.5$.

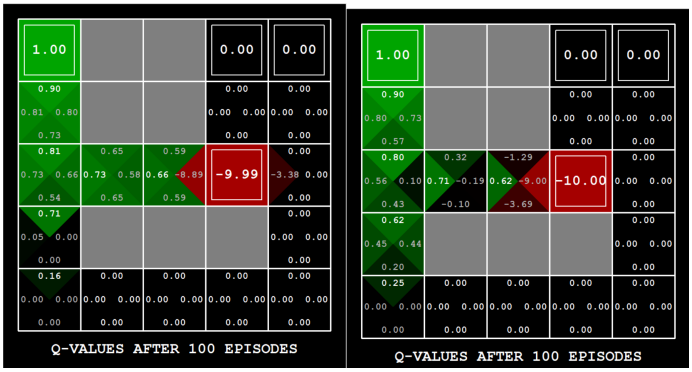
In the *gridworld.py* experiments we found that Sarsa(λ) performed better per episode than Q-learning due its eligibility trace allowing for each training episode to update more of the Q-values than Q-learning's single step functions. Figure 4 clearly illustrates the difference. After only 10 training episodes, a majority of the Q-values have been updated at least once by the Sarsa(λ) agent; while the Q-learning agent has only updated a few of its Q-values.

The ability to update the Q-values associated with each $(state, action)$ in the eligibility trace allows for good de-



(a) Q-learning agent Policy (b) Sarsa(λ) agent Policy

Fig. 3: Policies of the Q-learning and Sarsa(λ) agents after 10 episodes on the LargeMazeGrid. Sarsa(λ) agent's policy is almost on the verge of converging as opposed to that of the Q-learning agent.



(a) Q-learning agent Q values (b) Sarsa(λ) agent Q values

Fig. 4: Q values of the Q-learning and Sarsa(λ) agents after 100 episodes on the CustomGrid. Identical results are found for both the agents on this grid.

cisions be effect the value of the prior decisions, and thus speeds up policy convergence. It also, means that Sarsa(λ) is susceptible to noise, as a series of poor or random choices that lead to a positive outcome are *all* updated as though those decisions were good or meaningful to the final outcome. This leads the agent to get temporarily stuck in policies which are not optimal, meaning take longer to achieve the goal.

The other trade off of using the eligibility trace each time the agent picks an action, is the time needed to loop through all of the Q-values visited in the environment. For small simple environments such as *gridworld.py*, the trade off between training time and number of training episodes puts Sarsa(λ) ahead of Q-learning. However, in the more complex *pacman.py* environment the Sarsaλ) agent slows down considerably. Even though Figure 5 shows that Sarsa(λ) was able to reach peak win rate with fewer training episodes than Q-learning, the difference in real world training time was several hours.

V. Conclusion

From what we have already implemented, we can easily draw two conclusions:

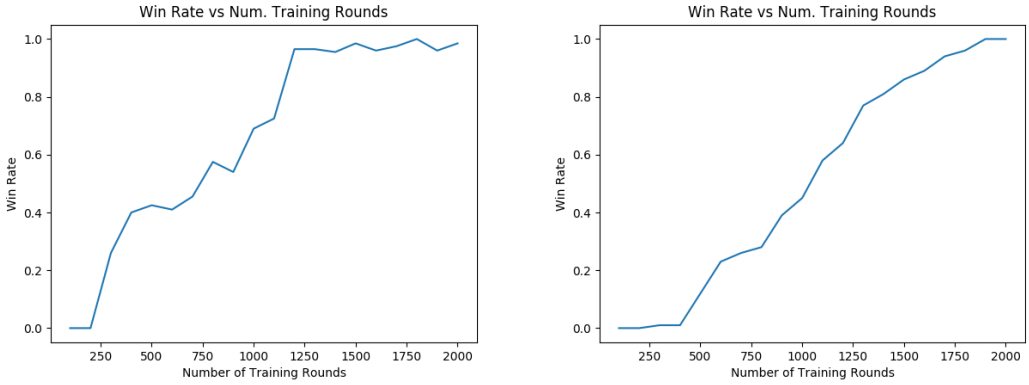
1. Q-learning maybe suffers from problems converging as a result due to it has higher per-sample variance than SARSA(λ), however SARSA(λ) learns a near-optimal policy while exploring. So if we decide to use SARSA(λ), we need propose a good strategy to decay in -greedy action choice, which can become fiddly hyper parameter to adjust.

2. SARSA(λ) is more conservative than Q-learning, because SARSA will approach convergence allowing for all kinds of penalties while agent explores its move while the Q-learning ignore them. In another words, if there is risk of a large negative reward close to the optimal path, Q-learning will perform more aggressive and will trigger that reward risk. On the contrary, SARAS will try to avoid it and slowly learn to use it.

All in all, Q-learning learn optimal policy directly and SARSA(λ) learn online. If you want to train agent in low-cost and fast0iterating environment, choose Q-learning. And if you care about reward risks while learning, SARAS will be the best choice compared Q-learning.

References

[1] D. Klein, J. DeNero, and P. Abbeel. Uc berkeley cs188 intro to ai, 2014.
[2] R. S. Sutton and A. G. Barto. *Reinforcement learning: An introduction*. MIT press, 2018.



(a) Q-Learning Agent

(b) Sarsa(λ) Agent

Fig. 5: Win rate vs training episodes for Q-learning and Sarsa(λ) agents. Each agent was trained using pacman smallGrid environment. Win rate was taken from 20 post training episodes. Each agent was trained with $\epsilon = 0.05, \gamma = 0.8, \alpha = 0.2$. The Sarsa($\lambda$) agent has a default $\lambda = 0.8$.