# Evaluation of SARSA($\lambda$) Learning Agent

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***Abstract*—This project compares exact and approximate versions of $Q$-Learning and the SARSA($\lambda$) algorithm. We examined the performance and accuracy of each in two settings: *gridworld*, and *pacman*. Gridworld is a small environment; here, SARSA($\lambda$) performed better (likely due to its ability to update multiple $Q$-values per action) but took longer to train. However, we also found that SARSA($\lambda$) was more sensitive to noise. Pacman is a more complex environment, and SARSA($\lambda$) slows down considerably. Both algorithms were able to do extremely well by the end of training ( nearly 100% winrate); SARSA($\lambda$) reaches this upper bound perfectly, while $Q$-learning does not. However, given $Q$-learning's much smaller training time, if a small amount of error is tolerable, then $Q$-learning is the better option.**

## 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 problems without requiring adaptations, it only needs stochastic transitions and rewards. $Q$-learning has its drawbacks, however: one in particular is 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 with a much smaller number of episodes. By successfully implementing the agent in our individual project 3, we already had a good understanding of this method. It also has its limitations. For example, not matter what 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($\lambda$) 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($\lambda$) is the SARSA algorithm with eligibility tracing. In this group project, we compare approximate SARSA($\lambda$) and approximate $Q$-learning.

## II. Background

The SARSA algorithm is an example of an On-Policy algorithm for TD-Learning [2]. The speciality of this algorithm compared to Q-Learning is that in the next state, maximum reward does not 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 a new reward. The name SARSA actually comes from the five inputs to the $Q$-value function, $Q(s, a, r, s', a')$. $s$ 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 Algorithm 1 and Figure 1, two action selection steps are needed for determining the next state-action pair along with the first. The parameters $a$ and $r$ do not change as they do in $Q$-Learning. The nature of the policy's dependence on $\mathcal{Q}$ determines the convergence properties of SARSA algorithm. For example, one could use $\epsilon$-soft or $\epsilon$-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($\lambda$) Algorithm with Dutch Tracing. Algorithm was provided by Sutton et al. [2]

## III. SARSA($\lambda$) Implementation

We chose to start with the codebase provided by UC Berkeley's Pacman-themed AI tutorial [1], and compare the SARSA($\lambda$) algorithm to the $Q$-learning algorithm without eligibility tracing. As the SARSA($\lambda$) algorithm requires an eligibility trace, we implemented this as a Python dict with default value of 0, like our $Q$-table. Unlike the $Q$-table, the eligibility trace must be cleared between episodes, so we clear

```
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($\lambda$) 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.

| Agent | Time(s)/100 eps | 50% Win Rate | Value convergence |
|---|---|---|---|
| SARSA($\lambda$) | 1678.92s | 1000 eps | 256 eps |
| $Q$-Learning | 3.54s | 800 eps | 4096 eps |
| Approximate $Q$-Learning | 1.92s | 800 eps | N/A |
| Approximate SARSA($\lambda$) | 896.32s | 1200 eps | N/A |

TABLE I: Summary of measured differences between SARSA($\lambda$) 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 *grid world.py* on the BookGrid world.

the values of the eligibility trace at the beginning of each training episode. To test and demo the SARSA($\lambda$) agent, we used a test that was built-in, and used by UC Berkeley which consisted of a small, grid world 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($\lambda$) 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 $\epsilon$-greedy function, our results for the basic set learning rate worked very well in grid world.

## IV. Results

Once the SARSA($\lambda$) 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($\lambda$) agent compared to the $Q$-learning agent already present.

For the this paper, we evaluated policy/value convergence in *grid world.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 layout visualizations. CustomGrid and LargeMazeGrid to test and compare the two agents. The LargeMazeGrid is a $20 \times 20$ grid with multiple deadends and a single reward. We ran both the agents for 100 episodes (with default values and 0 noise) and the SARSA($\lambda$) agent out-performed the $Q$-learning agent on this grid. For the SARSA($\lambda$) 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($\lambda$) agent was 0.18s, while the $Q$-learning agent took 0.29s.

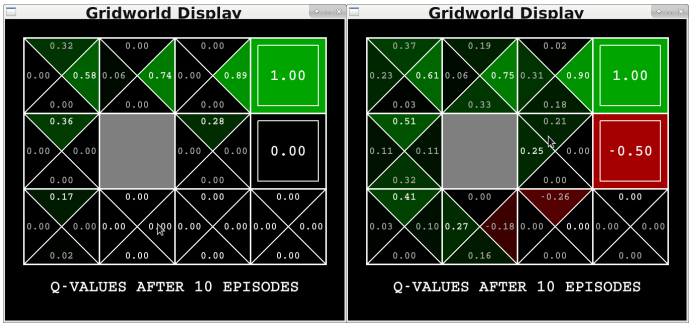
The CustomGrid is a $5 \times 5$ grid, with a small reward near the start point and a large reward further away, with a couple hazards along the way. We ran both the agents for 1000 episodes (with default values and 0 noise). Both the agents performed identically on this grid. With the small reward being near the start, both the agents deviated towards it and did not 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 $\lambda = 0.8$.

Table I shows a summary of the experimental results. In general we found that the SARSA($\lambda$) agent outperformed the $Q$-learning agent in the grid world. SARSA($\lambda$) was able to converge on an optimal policy 3840 training episodes before the $Q$- learning agent. On the other hand, the SARSA($\lambda$) 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($\lambda$) agent was able to reach a consistent 100% win rate before the $Q$-learning agent.

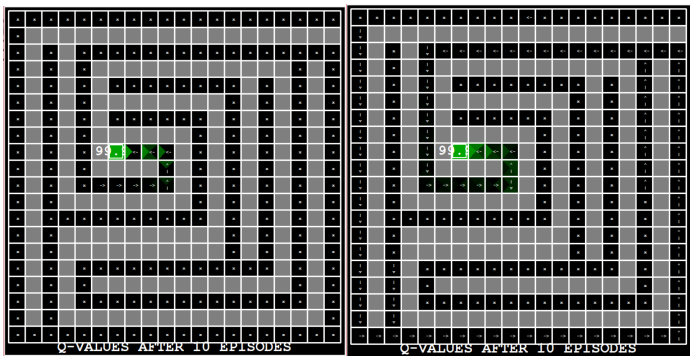
In the *gridworld.py* experiments we found that SARSA($\lambda$) performed better per episode than $Q$-learning due its eligibility trace allowing for each training episode to update more of the $Q$-values than $Q$-learning's single step functions. Figure 2 and Figure 3 clearly illustrate the difference. After only 10 training episodes, a majority of the $Q$-values have been updated at least once by the SARSA($\lambda$) 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 decisions be affect the value of the prior decisions, and thus speeds up policy convergence. It also, means that SARSA($\lambda$) 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 it takes longer to achieve the goal.




(a) $Q$-learning agent $Q$ values (b) SARSA($\lambda$) agent $Q$ values

Fig. 2: $Q$ values of the $Q$-learning and SARSA($\lambda$) agents after 10 episodes of training. The SARSA($\lambda$) 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 $\epsilon = 0.5$.




(a) $Q$-learning agent Policy (b) SARSA($\lambda$) agent Policy

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

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($\lambda$) ahead of $Q$-learning. However, in the more complex *pacman.py* environment the SARSA($\lambda$) agent slows down considerably. Even though Figure 5 shows that SARSA($\lambda$) was able to reach peak win rate within the allotted training episodes, the difference in real world training time was several hours.

## V. Conclusion

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

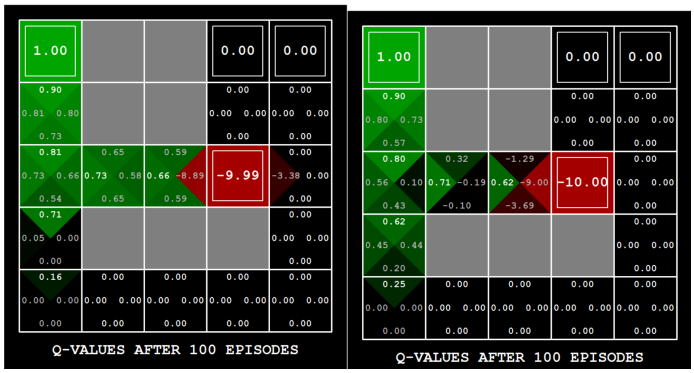
1. $Q$-learning suffers from problems converging as a result of having a higher per-sample variance than SARSA($\lambda$); however SARSA($\lambda$) learns a near-optimal policy while exploring. So if we decide to use SARSA($\lambda$), we need to propose a good strategy to explore alternative paths, as might occur with $\epsilon$-greedy action choice. A drawback is that this can become a fiddly hyper-parameter to adjust.

2. SARSA($\lambda$) is more conservative than $Q$-learning, because SARSA will approach convergence allowing for all kinds of penalties while agent explores. The $Q$-learning algorithm ignore this. If there is risk of a large negative reward close to the optimal path, $Q$-learning will react more aggressively and will avoid the area associated with that risk. On the contrary, SARSA($\lambda$) will try to avoid it and slowly learn to use it.

3. When both algorithms use linear function approximation, $Q$-learning converges faster than SARSA($\lambda$) but at the end of the training SARSA($\lambda$) seems to have a winrate of 1.0 as opposed to LFA $Q$-learning, which is high, but does not remain at 1.0.

$Q$-learning seems to learn at a far lower computational cost per episode, but SARSA($\lambda$) converges faster each episode, implying that if you are doing machine learning in the real world, where episodes can take a comparatively very long time, SARSA($\lambda$) should be your choice over $Q$-learning.

However, with LFA, SARSA($\lambda$)'s performance per episode drastically decreases. The plateau at 1.0 success rate at the end of the graph suggests that it may still be desireable if the above is true and a .01 failure rate is unacceptable, but $Q$-learning with LFA will perform far better in fewer episodes, and perhaps orders of magnitude less computational cost.

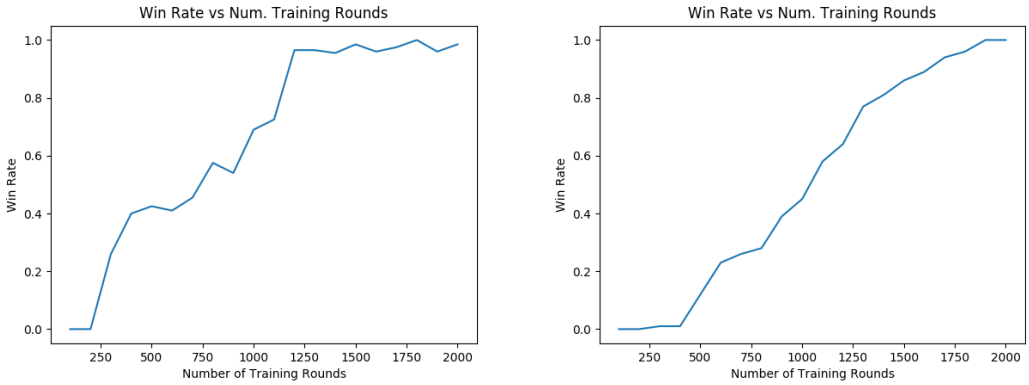



(a) $Q$-learning agent $Q$ values (b) SARSA($\lambda$) agent $Q$ values

Fig. 4: $Q$ values of the $Q$-learning and SARSA($\lambda$) agents after 100 episodes on the CustomGrid. Similar results are found for both the agents on this grid.

## VI. Team Effectiveness

We met soon after the team project was assigned, all having done the related homework, and done the SARSA($\lambda$) algorithm. Building the team had been a somewhat slow process, but we managed to find each other and put us all in one group chat, which was a wise decision as now we were all able to communicate instantly and directly with one another. In the meeting, we decided what our general roles would be, and set to work. Despite our team chat, however, we still had minor communication issues, as some of us missed the messages one way or another. Our biggest mistake was misunderstanding




(a) $Q$-Learning Agent

(b) SARSA($\lambda$) Agent

Fig. 5: Win rate vs training episodes for $Q$-learning and SARSA($\lambda$) 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 $\lambda = 0.8$.

the instructions, setting out to describe the differences of SARSA($\lambda$) and $Q$-learning without LFA. Luckily, we were able to spot our mistake, and run some tests displaying how the 2 compare with LFA.

## VII. Source Code

The source code is avaible at *https://github.com/Parsons-Ray/CSE571-Group-Project*.

## 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.